Asymmetric shocks, persistence in volatility and spillover effects between non ferrous metals on the LME spot market

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Abstract

This paper employs a VAR(1)-GARCH(1,1) model to examine whether there is evidence of asymmetry shocks, persistence in volatility and spillover effects between three reference non-ferrous metal traded on the London Metal Exchange (Nickel, Lead and Copper) on the spot market using monthly data for the January 1980 to June 2013 period. This study illustrates dissymmetric effects on Nickel and Lead volatilities of bad and good news. Those non-ferrous metals reacted more actively to negative shocks as stocks markets. For return and volatility spillover, results show significant transmission among base metals. Regarding the return-generating process, past values of metal returns prices largely determined their current values at different levels and turning to the conditional variance equations, sensitivity to their past conditional volatility appears to be significant for the metal prices, implying that past variances returns increased current volatility of metal returns. We also find that past news from Nickel strongly affected the volatility behaviour of Copper and vice versa.

1. Introduction

1.1. Non ferrous metal market

Due to differences in market structures, price recognition methods, as well as quantities produced, metal markets are often separated into five groups: Base Metals or non ferrous metals, Steel and Ferro-Alloys, Minor Metals, Platinum Group Metals (PGMs) and Precious Metals Excluding platinum, palladium and other PGMs.

The global market for base metals can be considered as the most developed of any group of metals. Now markets with trading desks around the world settle transactions, equaling trillions of dollars each year. Forward and option contracts, as well as electronic trading, have all contributed to a more efficient market. That is, one that can more effectively determine what buyers and sellers are willing to pay for a particular metal. Consequently, the difference between bid and offer prices for standard base metals is normally much smaller than what one would see for other metals.

The prices of individual non ferrous metals, like prices for any commodity, are essentially determined by supply and demand. However, to assume that information on supply (production and inventories) and demand (consumption) is readily available, accurate and transparent, would be a big mistake, regardless of the type of metal.

Price determination mechanisms range from advanced spot and forward contracts traded online as well as in London at the London Metal Exchange (LME) or in New York at the New York Mercantile Commodity Exchange (COMEX) to basic cash exchanges between buyers and sellers. Then, movements of metal commodity prices are expected to be understood by analyzing some supply and demand constraints:

On the one hand, Chinese import demand affects metal bases prices. they fell by 2.5 percent in February 2014 due to concerns about slowing demand in China following weaker than expected economic data—including a sharp drop in metal imports in February which was likely affected by Chinese New Year.

In June 2013, the largest decrease was for iron ore, down 7 percent and more than 25 percent the past four months, on rising production and concerns about slowing demand in China for construction and infrastructure. At the same time China's electronics sector has a significant influence on tine prices.

The booming car industry in Asia, the US and Europe pushed the demand of lead in January 2013. At month's end prices jumped even clearly above the line of USD 2.400/t.

On the side of supply, many events contributed to raise metals prices. Weather-related supply constraints in Brazil and Western Australia where cyclones closed three major ports. As well as in China, a cold winter has impacted domestic ore production. All those events are important constraints which impacted metal prices in January 2013.

Furthermore, the continued supply contraction in Indonesia, the world's largest tin producer affects tin prices.

A strike in all ports in Chile which is Worldwide the major export country of copper caused pushed prices up again in January 2014. In March of this year, news about a possible military conflict between Russia and the Ukraine led to a price crash. Metals had been impacted by this scenario as well and consequently Copper quotations on the LME dropped below USD 7.000/t which was the lowest level since beginning of December.

1.2. Non-Ferrous Metal Industry

At least 42 non-ferrous metals plus ferro-alloys and carbon and graphite are produced in EU and are used in a variety of applications in the metallurgical, chemical, construction, transport and electricity generation/transmission industries. These metals are often used in sectors that are expanding in tandem (John and Jerrett, 2008). For example high purity copper is essential for electricity generation and distribution and small amounts of nickel or refractory metals improve the corrosion resistance or other properties of steel. They are also used in many high technology developments, particularly in the defence, computing, electronic and telecommunications industries.

On the supply side, base metals are often joint outputs from individual mining operations. The London Metal Exchange (LME) is the major international market for the main industrially-used non ferrous metals. It is used worldwide by producers and consumers of non-ferrous metals as centre for spot, futures and options trading in these metals. Thus, there are strong economic linkages—supply and demand-side—to explain why volatility spillovers between LME metal prices may be present.

In Europe, ore deposits that contain metals in viable concentrations have been progressively depleted and few indigenous sources remain. Most concentrates are therefore imported from a variety of sources worldwide. Recycling constitutes an important component of the raw material supplies of a number of metals. Copper, aluminium, lead, zinc, precious metals and refractory metals, among others, can be recovered from their products or process residues and can be returned to the production process without loss of quality in recycling. Overall, secondary raw materials account for a high proportion of the production, thus reducing the consumption of raw materials and energy.

The structure of the industry varies metal by metal. No companies produce all non-ferrous metals although there are a few pan-European companies producing several metals, e.g. copper, lead, zinc, cadmium, etc.

Metal prices are not only important to manufacturers and end-users. The accurate representation and empirical modelling of metals commodity markets volatility and preciously non-ferrous metals is a very important matter, as volatility causes uncertainty to producers with regard to revenues, costs and margins (Morales, 2008). The interest in commodity markets is that they are an outlet for speculative activities and therefore for the implementation and evaluation of trading and hedging strategies, and the conduct of risk management, McMillan and Speight (2001).

This paper examines whether there is evidence of asymmetry, persistence of volatility and spillovers effects between three reference LME non-ferrous metal commodities namely Nickel, Lead and Copper by using a VAR(1)-GRJ-GARCH(1,1). For the analysis the monthly data about the commodity spot price series are collected during a sample period from January of 1980 to June of 2013.

2. Brief review of literature on volatility on the non-ferrous metals markets

Several published empirical papers analyze aspects of spot and future pricing for non-ferrous metals. Majority was focused on the LME. Non-ferrous metal markets, including those for aluminium, aluminium alloy, copper, lead, nickel, tin and zinc, are frequently the subject of empirical analysis. Properties of precious metals markets, namely gold, silver, and platinum and palladium have also been investigated. Empirical research involving non-ferrous metals spot and futures markets can be classified into four broad areas (Watkins and Mc Aleer, 2003): market efficiency, the theory of storage and cost-of-carry mode, price volatility and risk and other aspects of metals markets.

Empirical studies of price volatility and risk in non-ferrous metal markets include modelling the volatility of spot and future prices using a random walk model, or various GARCH processes, and the analysis of the risk to the return relationship in futures markets using a CAPM approach volatility of six LME spot markets has been analyzed by Brunetti and Gilbert (1995), and modelled using a FIGARCH process by Brunetti and Gilbert (1997). All six metals were found to have similar volatility processes. Increased speculative activity over a long sample period does not appear to have led to increased volatility.

COMEX copper futures price volatility is examined by Bracker and Smith (1999) using various GARCH specifications, in which GARCH and EGARCH were found to be superior to the GRJ-CARCH, AGARCH model and a random walk model. Both AGARCH and GRJ-GARCH allow large negative shocks to have a greater effect on the conditional variance than large positive shocks, but the specification of the time-varying variance in each model is different. The GRJ-GARCH allows shocks to have a greater asymmetric effect than does AGARCH. A CAPM approach returns commensurate with the systematic risks in each market.

McMillan and Speight (2001) analyzed the time-varying volatility of daily non-ferrous LME settlement prices (aluminium, copper, nickel, lead, tin and zinc) over the period 1972-1995. Their investigation provided a decomposition of volatility into its long-run and short-run components. Their main findings are that the half-life of shocks to markets-driven short-run volatility typically extends over periods of no more than 8 days, while the half-life of shock to fundamentals-driven long-run volatility extends over periods of up to 190 days, such that metals price volatility is only very slowly mean-reverting. Also, their findings show superior results of their model in comparison with the standard model of conditional volatility widely used in modelling financial market volatility. Their results confirmed the relevance and significance of the decomposition of metals price volatility and the presence of three separate principle components driving underlying metals volatility.

Bernard and al (2005) analyzed aluminium price series with daily, weekly and monthly frequencies. They used three econometric specifications: random-walk models with ARCH or GARCH effects, Poisson-based jump-diffusion models with ARCH or GARCH effects and mean reverting models that allow for uncertainty in equilibrium price. Their estimates showed that in the case of high frequency (daily and weekly) data, the mean-reverting model with stochastic convenience yield outperforms to a large extent. All other competing models for all forecast horizons, within the class of non-mean reverting GARCH processes analysed for the same frequencies models with jumps or asymmetries fare best, yet the latter remain dominated by the mean reverting models. With monthly data, the mean-reverting model still fares well in comparison with the random-walk GARCH class.

Watkins and McAleer (2006) analysed data on 3-month futures contracts for aluminium, aluminium alloy, copper, lead, nickel, tin and zinc. They estimated various long-run models using daily London Metal Exchange price data for the period 1 February 1986 to 30 September 1998. They found that in most of the samples considered for the seven metals markets, the test for co-integration determined the existence of one statistically significant long-run relationship among the futures price, spot price, stock level and interest rate. They also found that the risk premium and carry models usefully are applied to each of the LME metals markets over different time periods.

Copper futures markets have been studied extensively in various international studies. Li and Zhang (2008) investigate the time varying relationship using rolling correlations and rolling Granger Causality followed by co-integration test. The results of co-integration test show that there is a long run relationship between SHFE and LME copper prices. Li and Zhang (2009) examine the relationship between copper traded on Shanghai Futures Exchange and London Metal Exchange using co-integration and Markov Switching VECM model. They find a long run relationship between the two copper futures markets and the influence of LME is stronger is SHFE than vice versa. The same authors in an earlier piece of work,

Bulut B (2010) investigates the univariate models for prices of six non-ferrous metals. Results find that the price series contain time varying variance. Then author assess the forecasting performance of GARCH models for aluminium, copper, lead, nickel, tin, and zinc future prices in LME. He employs daily data for the period December 12, 2003 – December 15, 2008 and model the volatility process via GARCH, EGARCH, and TGARCH models. Estimates show that the forecasting performances of all three models are similar. However, they suggest the use of the GARCH model because it is more parsimonious and has a slightly better statistical performance than the other two.

Cochran and al. (2012) examine the returns and the long-memory properties of the return volatilities of four base metals – copper, gold, platinum, and silver. Daily returns for the January 4, 1999 to March 10, 2009 period are used. Three key issues are addressed: (1) whether the volatility processes exhibit long-run temporal dependence; (2) whether the returns and conditional volatility of returns are affected by the uncertainty brought about by the financial crisis in September 2008; and (3) whether the implied volatility in the equity market, as measured by VIX, plays a significant role in determining metal risk and return. The results show that VIX is important in the determination of metal returns and return volatility. The findings also suggest that metal and equity returns are influenced by a common risk factor and failure to explicitly model this factor will yield less than optimal portfolio diversification. Events during the post-September 1, 2008 period contributed to increase return volatility for several of the metals. .

Sinha and Mathur (2013) attempt to prove the linkages in price, return and volatility behaviour of base metals (aluminium, copper, nickel, lead and zinc) which are traded on Indian commodity exchange. Links between Multi Commodity Exchange (MCX) and London Metal Exchange (LME) are analysed through three models: Price – Co-integration methodology and Error Correction Mechanism Model (ECM), Return and Volatility – Modified GARCH model, Return and Volatility - ARMA-GARCH in mean model – Innovations Model. The findings of the paper suggest that there exists a strong linkage across the price, return and volatility of futures contracts traded on MCX and LME respectively.

More recently, Todorova and al (2014) employs a multivariate heterogeneous autoregressive (HAR) model to consider the volatility spillovers between the five of the most liquid and important non-ferrous metals contracts (Aluminum, Copper, Lead, Nickel, and Zinc) traded on the London Metal Exchange using intraday data over the period June 2006–December 2012. The results show that the volatility series of other industrial metals appear to contain useful incremental information for future price volatility. However, the own dynamics are often sufficient for describing most future daily and weekly volatility, with the most pronounced volatility spillovers identified in the longer term. Combined together, the results in this study provide useful findings for exporter and importer countries dealing with the continuing volatility in these industrially important commodity markets.

3. Econometric approach

In many empirical literatures, news flow across markets through returns (may not be significant and visible; however, it may have a high volatility effect. Volatility has been considered a better proxy of information by Clark (1973), Tauchen and Pitts (1983) and Ross (1983). The ARCH model, which was developed by Engle (1982) and later generalized by Bollerslev (1986) by including lagged term conditional volatility, is one of the most popular methods for modeling the volatility of high-frequency financial time series data.

Multivariate GARCH models with dynamic covariances and conditional correlation, such as the BEKK parameterization, CCC (constant conditional correlation) or DCC (dynamic conditional correlation) models, have been shown to be more useful in studying volatility spillover mechanisms than univariate models. The estimation procedure in univariate models becomes extremely difficult, especially in cases with a large number of variables, due to the rapid proliferation of parameters to be estimated

Due to the failures of the MGARCH model, the VAR-GARCH model was chosen to allow for a focus on the interdependence of the conditional returns, conditional volatility and conditional correlations between commodity markets. VAR(k)-GARCH(p,q) was proposed by Ling and McALeer (2003) and later applied by several researchers, such as Chan and al. (2005), Hammoudeh and al. (2009) and Arouri and al. (2011).

This model includes the multivariate CCC-GARCH of Bollerslev (1990) as a special case in which correlations between system shocks are assumed to be constant to ease the estimation and inference procedure. This method permit an investigation of the conditional variance and conditional correlation cross effects with meaningful estimated parameters and less computational complications relative to the other methods. In this paper, the trivariate VAR(1)-GARCH(1,1) model was used to explore the joint evolution of returns links, asymmetric volatility and correlations among the metal returns.

The conditional mean equation of the VAR(1)-GRJ-GARCH(1, 1) system is given by:

$$\begin{aligned} R_t &= \varphi R_{t-1} + \mu_t \\ \mu_t &= h_t^{1/2}\eta_t \end{aligned} \qquad [1]$$

Where :

$$R_t = \begin{pmatrix} r_{1t} \\ r_{2t} \\ r_{3t} \end{pmatrix} = \begin{pmatrix} \Delta \ln PNick \\ \Delta \ln PLead \\ \Delta \ln PCopp \end{pmatrix}$$

$$\mu_t = \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \end{pmatrix} \quad \eta_t = \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \\ \eta_{3t} \end{pmatrix} \quad h_t^{1/2} = \mathrm{Diag}\left(h_{1t}^{1/2} \quad h_{2t}^{1/2} \quad h_{3t}^{1/2}\right)$$

- r_{1t}, r_{2t} and r_{3t} are the Nickel, Lead and Copper return at time t, respectively.
- μ_{1t}, μ_{2t} and μ_{3t} are the residual of the mean equations for the Nickel, Lead and Copper at time t, respectively.

- η_{1t}, η_{2t} and η_{3t} refer to the innovation and is an i.i.d. distributed random vector.
- h_{1t}, h_{2t} and h_{3t} are the conditional variances of r_{1t}, r_{2t} and r_{3t}, given by :

$$h_{i,t} = C_i + \alpha_{i,i}\mu_{i,t-1}^2 + \beta_{i,i}h_{i,1t-1} + \sum_{j=1}^{2}\alpha_{i,j}\mu_{j,t-1}^2 + \sum_{j=1}^{2}\beta_{i,j}h_{j,t-1} + \gamma_i\mu_{i,t-1}^2 S_{i,t}^- \quad [2]$$

Equations (2) show how volatility is transmitted over time across the metal prices. The cross value of the error terms represents short run persistence (or the ARCH effect of past shocks), which captures the impact of the direct effects of shock transmission. The presence of h_t captures the volatility spillovers or interdependencies between commodity markets and the stock exchanges. It is the contribution to the long-run persistence (or the GARCH effects of past volatilities).

The conditional covariance between metal returns is as follows:

$$\left[h_{ij}\right]_t = \rho.\sqrt{h_{it}}.\sqrt{h_{jt}} \quad [3]$$

Where ρ is the constant conditional correlation. To examine the return and volatility spillover mechanism across the considered markets, the quasi-maximum likelihood (QML) method was employed to estimate the parameters of the VAR(1)-GRJ-GARCH(1, 1) model.

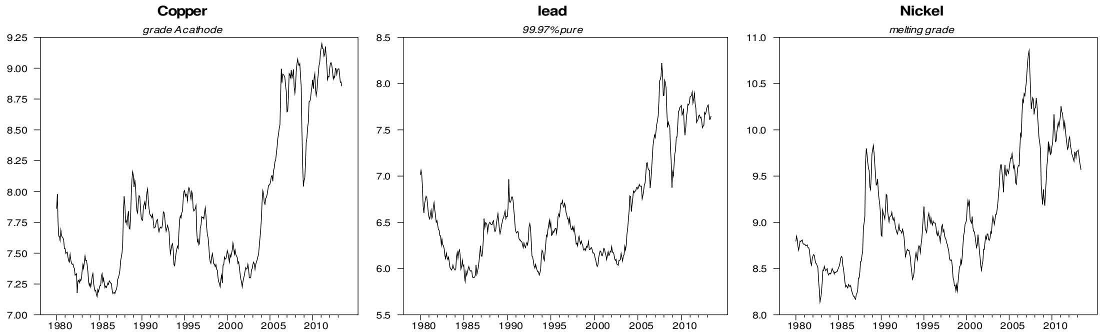
4. Empirical Results

4.1. Data and Descriptive Analysis

We use monthly data corresponding to the average of closure values of metal prices expressed in U.S. dollar, from January 1980 to June 2013 (see Figure 1). Metal prices extracted from World Economic Outlook (IMF) concern three reference metals namely Nickel, Lead and Copper. The figure clearly shows that the price indices vary over time. Moreover, there have been increases in the correlation between metal prices. However, the 2000 decade was characterized by large fluctuations in metal prices. First, the figure indicates that all the metal prices in US Dollar behaved in a similar manner.

Figure 1 : Metal Log-Prices

Jan 1980 - Juin 2013



Source : World Economic Outlook

Those three series are clearly non-stationary (Table 1) according to ADF and PP Unit Root Tests.

<u>Tableau1</u>: Unit root tests of log-Prices

Metals	NICKEL		LEAD		COPPER	
	Constant only	Linear trend	Constant only	Linear trend	Constant only	Linear trend
ADF	-1.96664	-3.01933	-1.11386	-2.85243	-1.18011	-2.86946
PP	-1.58622	-2.43864	-0.87846	-2.59539	-0.74614	-2.27615

<u>Source:</u> World Economic Outlook, Authors regressions

<u>Note:</u> *, **, and *** denote significance levels of 10%, 5% and 1%, respectively

It is impossible to use data directly extracted from the database as mean, variance and autocorrelation structures change over time. Therefore, in order to ensure stationarity Nickel, Lead and Copper returns are defined as continuously compounded or log returns[1] (Figure 2) at time t, r_t, calculated as follows:

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

Where P_t and P_{t-1} are metal prices for months t and t-1, respectively

All classic unit root tests confirm that log-returns are stationary. The mean and variance of the series are constant across time.

[1] Log-returns are generally known as stationary

Tableau 2: Unit root tests of log returns

Metals	NICKEL		LEAD		COPPER	
	Constant only	Linear trend	Constant only	Linear trend	Constant only	Linear trend
ADF	-12.0738**	- 12.0590**	-12.9186**	-13.0140**	-12.1088**	-12.1148**
PP	-14.1089**	-14.1105**	-16.2149**	-16.3229**	-14.0068**	-14.0664**

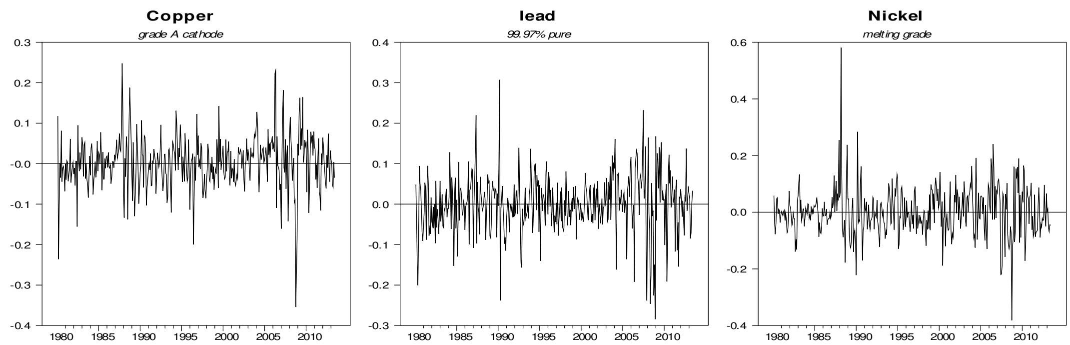
Source: World Economic Outlook, Authors regressions

Note: *, **, and *** denote significance levels of 10%, 5% and 1%, respectively

Figure 2 depicts the monthly movements in the metal returns from January 1980 to July 2013. Notice that volatility clustering can be easily observed from Figure 2 where large changes follow large changes of either sign and small changes follow small changes.

Figure 2 : Metal Returns

Jan 1980 - Juin 2013



Source : World Economic Outlook

Descriptive statistics are reported in Table 3. The sample means of Nickel, Lead and Copper returns are positive. The characteristics of the log-returns series used in our data set presented suggest the existence of non-normality and fat tails.

The Jarque-Bera test rejects the null hypothesis that log-returns are normally distributed: the p-values for all metal returns above are zero. This is also evident from excess kurtosis coefficient of the data which indicates that metal returns are leptokurtic relative to normal distribution.

All metals report negative skewness except Nickel. Therefore, the dataset includes two out of three metals for which returns are skewed to the left. This means that the mass of the distribution is located on the right and that the mean is lower than the median.

Tableau 3: Summary Statistics of Metal Returns

	Metals		
	Nickel	Lead	Copper
	Panel A: Descriptive Statistics of each monthly return series		
Mean	0.001930	0.001587	0.002477
Standard Error	0.084672	0.072320	0.065035
Kurtosis (Excess)	6.224312	3.238304	4.048252
Skewness	0.754322	-0.274121	-0.429290
Jarque-Bera	685.343426	84.225581	286.138675
	Panel B : ARCH Tests		
LB (8)	4.627	5.223	18.125**
LB^2 (8)	18.195**	88.579***	19.008**
ARCH-LM(8)	15.447310*	70.957381***	21.482077***

Source: World Economic Outlook, Author's regressions

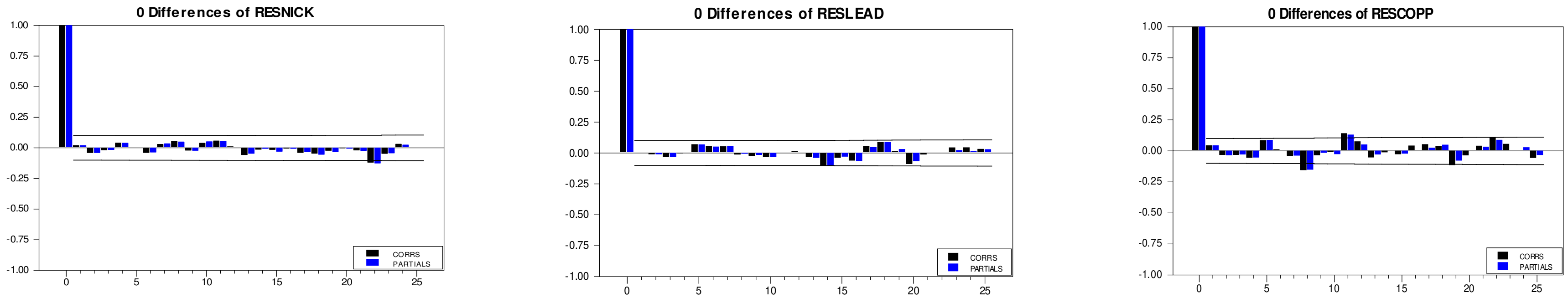
Note: *, **, and *** denote significance levels of 10%, 5% and 1%, respectively. LB(8) and $LB^2(8)$ are the Ljung-Box statistics applied on returns and squared returns, respectively. ARCH-LM(8) is a Lagrange multiplier test for ARCH effects up to order 8 in the residuals (Engle, 1982)

Before we conduct the GARCH tests we test for the existence of ARCH effects in the data sets. The results are shown in Table 3 and display clear evidence of significant ARCH effects in all of metal prices. The Ljung-Box statistic[2] for 8 lags applied on returns indicates that significant linear dependencies exist. Furthermore, the Engle (1982) ARCH-LM[3] test statistics for 8 lags was conducted in order to test the null hypothesis of no ARCH effects. The test statistics are statistically significant at one per cent level, implying that there exist significant ARCH effects on the data at all frequencies. Even the analysis of autocorrelations graphs show that only Nickel and Lead returns don't present dependence in residuals.

[2] To detect linear dependency, we find autocorrelations between squares of residual from regression : $\ln P_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j \beta \ln P_t + \varepsilon_t$

[3] to test the null hypothesis of no ARCH effects, we can use Engle (1982) ARCH-LM test statistics as follows TR^2 based on the regression: $\hat{\varepsilon}_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \hat{\varepsilon}_{t\ i}^2 + \nu_t$

Figure 3: autocorrelations and partial autocorrelation of Residuals

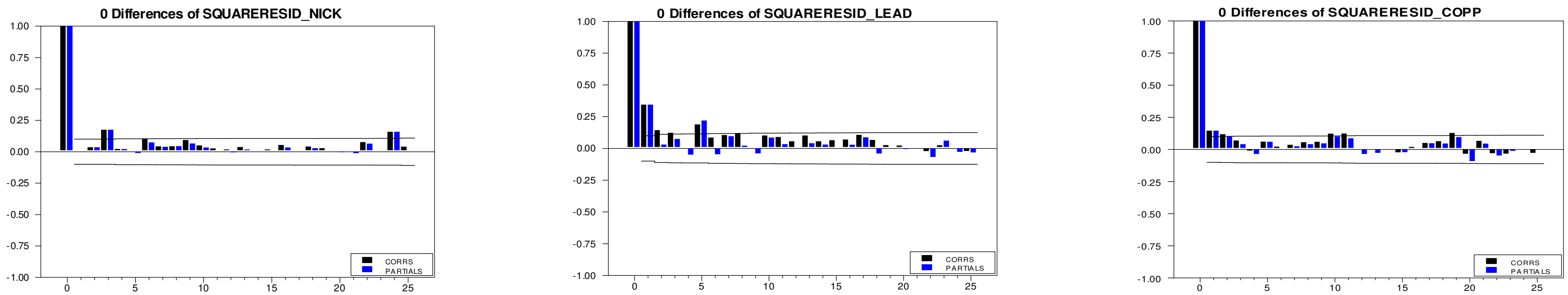


NICKEL LEAD COPPER

Source: World Economic Outlook, Author's regressions, WinRats Pro

Note: Autocorrelations and partial autocorrelations are in black and blue, respectively

Figure 3: autocorrelations and partial autocorrelation of square of Residuals



NICKEL LEAD COPPER

Source: World Economic Outlook, Author's regressions, WinRats Pro

Note: Autocorrelations and partial autocorrelations are in black and blue, respectively

4.2. Variance asymmetry, spillovers and persistence

Using the three monthly prices from January 1980 to June 2013 under investigation, Variance asymmetry, spillover and persistence are examined in this section using a multivariate VAR(1)-GRJ-GARCH(1,1) model estimated with a student distribution of errors justified by Table 3. Estimation results are reported in Table 4.

Past returns determine current returns

In Table 4, regarding the return-generating process, past values of metal returns prices largely determined their current values at different levels. This influence suggests that past returns can be used to forecast future returns in of all metals, indicating short-term predictability in metal price changes. For all the metal return, the past returns influence the current return. This can be explained by the fact that access to London Metal Exchange is restricted to his members classified into seven categories specialized for a type of operation who react in the same manner to information that affects non-ferrous metals prices.

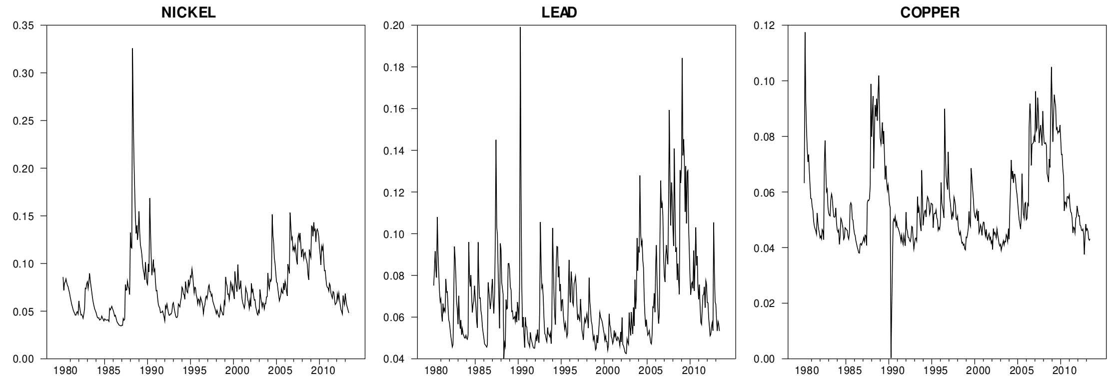
In terms of information transmission through returns, the Nickel returns are affected by the other metal returns. The highest metal's reaction to a price change is observed in Nickel. The change is equal to 13.2% due to a variation of 1% of copper price. This result indicates that information flows from the Copper market to Nickel market.

Significant volatility persistence exist on spot market of non-ferrous LME metal

Turning to the conditional variance equations, the estimated results of the GARCH coefficients are significant at conventional levels in all of the markets. Sensitivity to their past conditional volatility (h_{t-1}) appears to be significant for the metal prices, implying that past variances returns increase current volatility of metal returns. The Nickel price is the most volatile (0.509007998), followed by the Lead (0.462213280), while the Copper price at the tail end of the volatility ranking (0.389942221). This finding suggests that former conditional volatility values of these returns can be employed to forecast future volatility, and a GARCH(1, 1) model is adequate for capturing any persistence in the commodity markets' volatility.

Alternately, the current conditional volatility of the metal prices also depends on past shocks or news affecting return dynamics because is significant for Nickel and Copper prices. Coefficients of $(\mu_{t-1})^2$ is smaller for each metal than (h_{t-1}), the metal market's volatility, suggesting that a commodity market's former volatilities are more important in predicting future volatility than past shocks. Figure 3 show these properties by plotting the variations in the conditional variance over time for the metal prices. Return turbulence coincides with very volatile variance as we can see above. In this dataset, we can detect the presence of heteroskedasticity.

Figure 3 :Conditional variance VAR(1)-GRJ-GARCH(1,1) for the metal prices



Source : World Economic Outlook

Bad and good news have dissymmetric effects on Nickel and Lead volatilities

Furthermore, specification GRJ specification for VAR(1)-GARCH is pertinent because return variances for Nickel and Lead exhibit significant asymmetry. Coefficients of sensitivity to negative information ($\alpha_{ii} - \gamma_i$, cf. [2]) are 0.43 and 0.75 for Nickel and Lead returns respectively; coefficients of sensitivity to positive shocks ($\alpha_{ii} + \gamma_i$, cf. [2]) are 0.15 and 0.01 for Nickel and Lead returns respectively. Those findings suggest that non-ferrous metals markets react more actively to negative shocks as stocks markets. However, the absolute value of $(\mu_{t-1}^{Lead})^2 S_t^-$ (0.366949846) is greater than $(\mu_{t-1}^{Nick})^2 S_t^-$ (0.144562755), meaning that asymmetry is stronger for Lead.

Spillover effects between base metals

Considering the volatility spillover effect between metal's markets, results in table 4 show how past news from Nickel affects negatively the volatility behaviour of Copper and vice versa, with estimated coefficients of -0.086404612 and -0.092668036, respectively. Significant spillovers exist across the Nickel and Copper returns. However, the absolute value of $(\mu_{t-1}^{Copp})^2$ is greater than $(\mu_{t-1}^{Nick})^2$, implying that the spillovers from Copper to Nickel are more significant than the reverse direction[4], which means that the information flow from Copper to Nickel is stronger. The analysis of volatility interdependence shows significant volatility spillovers between metal returns.

As shown in Table 4, the estimates for constant conditional correlations (CCC) between the metal returns are all positive. However, the estimates demonstrate that the highest CCC is between Copper and Lead, suggesting more mutual responses in the economic factors between these metals than other metals.

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[4] Results show that past Nickel shocks have significant negative effects on metal returns volatility with estimated coefficient of -0.086404612. Even effect of Copper's lagged squared residual on Nickel's return is negatively significant (-0.092668036) at significance level of 10%

Table 4: Estimates of the trivariate VAR(1)-GRJ-GARCH (1, 1) model for the Metal Returns.			
Variables	Nickel	Lead	Copper
	$\Delta \ln PNick$	$\Delta \ln PLead$	$\Delta \ln PCopp$
Mean Equation			
$\Delta \ln PNick_{-1}$	0.283940967***	-0.041578164	-0.001461465
	(0.049865633)	0.034589982	0.024814025
$\Delta \ln PLead_{-1}$	-0.067803755*	0.205040983***	-0.029067995
	(0.038788667)	0.045251863	0.023491679
$\Delta \ln PCopp_{-1}$	0.132427972*	-0.008165078	0.299357183 ***
	(0.068906494)	0.055515745	0.053069192
Variance Equation			
C	-0.000198928**	0.000490958***	0.000257144***
	(0.000099254)	0.000028750	0.000009134
$(\mu_{t-1}^{Nick})^2$	0.291616996***	-0.013020753	-0.086404612***
	(0.004934738)	0.066365690	0.005840660
$(\mu_{t-1}^{Lead})^2$	-0.003069549	0.378028923	-0.069578562***
	0.027175766	0.003420566	0.005485197
$(\mu_{t-1}^{Copp})^2$	-0.092668036*	0.178380041***	0.165229273***
	0.034754149	0.066426655	0.009916865
h_{t-1}^{Niick}	0.509007998***	-0.417645869***	0.341260636***
	0.020909009	0.027813045	0.008541457
h_{t-1}^{Lead}	0.203380754***	0.462213280***	0.395579035***
	0.061362095	0.026296153	0.003514471
h_{t-1}^{Copp}	0.839905213***	0.993193518***	0.389942221***
	0.011647449	0.015091569	0.000109634
Asymmetry parameters			
$(\mu_{t-1}^{Nick})^2 S_t^-$	-0.144562755***		
	0.002547915		
$(\mu_{t-1}^{Lead})^2 S_t^-$		--0.366949846***	
		0.008676841	
$(\mu_{t-1}^{Copp})^2 S_t^-$			0.008241855
			0.008774689
CCC between Metal Returns			
Lead	0.382916104***	/	
	0.014812776		
Copper	0 0.467986979***	0.493163768***	/
	0.010310207	0.005751057	

Source: World Economic Outlook, Author's regressions

Notes; 1)*, **, and *** denote significance levels of 10%, 5% and 1%, respectively

2) Values in parenthesis are Standard Error Deviation

Finally, the estimated Ljung-Box statistics for the standardized and squared standardized residuals indicate that the Trivariate VAR(1)-GRJ-GARCH(1,1) model is correctly specified. Besides, the ARCH-LM tests indicate that only Nickel return dependence persists left in squared residuals (Figure 5). Hence, the results suggest that the Trivariate VAR(1)-GRJ-GARCH(1,1) model was reasonably well specified and most appropriate model to capture the ARCH (time-varying volatility) effects in the time series analyzed.

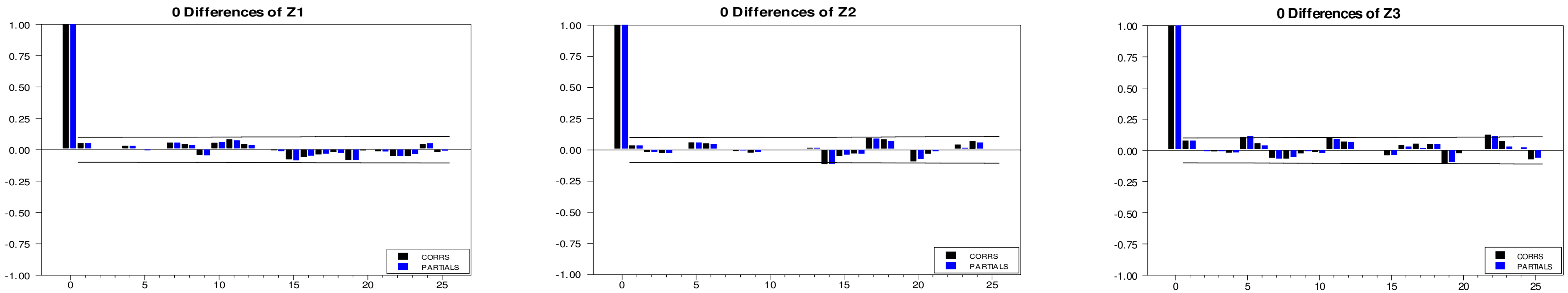
Table 4: Diagnostics on standardized and squared standardized residuals of VAR(1)-GRJ-GARCH(1,1)

	Returns		
	Nickel	**Lead**	**Copper**
LB (8)	3.530	3.930	13.318
LB^2 (8)	16.262	4.221	4.306
ARCH-LM(12)	14.372272*	4.428261	5.116710

Source: World Economic Outlook, Author's regressions

Note; *, **, and *** denote significance levels of 10%, 5% and 1%, respectively. LB(8) and $LB^2(8)$ are the Ljung-Box statistics applied on returns and squared returns, respectively. ARCH-LM(8) is a Lagrange multiplier test for ARCH effects up to order 8 in the residuals (Engle, 1982)

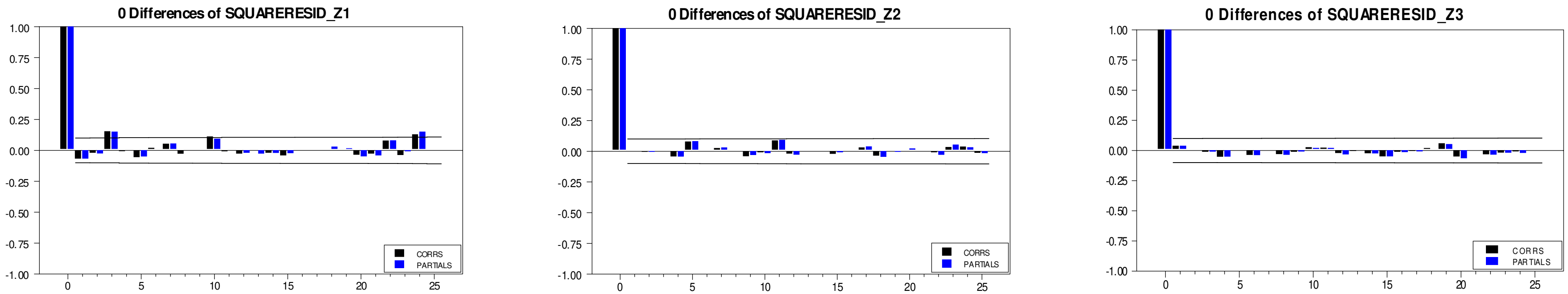
Figure 3: autocorrelations and partial autocorrelation of standardized Residuals



NICKEL LEAD COPPER

Source: World Economic Outlook, Author's regressions, WinRats Pro
Note: Autocorrelations and partial autocorrelations are in black and blue, respectively

Figure 3: autocorrelations and partial autocorrelation of squared standardized residuals



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Source: World Economic Outlook, Author's regressions, WinRats Pro
Note: Autocorrelations and partial autocorrelations are in black and blue, respectively

5. Conclusion

Analyzing volatility and spillover effects that exist between base metals can provide useful information for investors, traders, industries and governments who are concerned with the commodity markets, particularly with optimal hedging across these markets. This paper investigated the asymmetry shocks, persistence in volatility and spillover effects between three reference non ferrous metals Monthly returns from January 1980 to July 2013 of Nickel, Lead and Copper returns were analyzed using the VAR-GARCH model.
Empirical results of the volatility spillover mechanism between the markets analyzed in this study showed significant asymmetry shocks persistence and volatility transmission across base metals. Our findings corroborate previous studies showing significant volatility spillovers between base metals, such as Bulut B (2010), Cochran and al. (2012) and Todorova and al (2014).
Our results are crucial for financial market participants and building industry in particular for managing the cost of their input and forecasting future metal return volatility. This research can be extended to agri-commodities markets or used to analyze the transmission of volatility among spot, forward and futures markets.

6. References

Arouri M. Lahiani A. and Nguyen D.K., (2011), "Return and volatility transmission between world oil prices and stock markets of the GCC countries". *Economic Modelling* 28, 1815–1825.

Bernard J.T., Khalaf L.., Kichian M. and McMahon S., (2005),"Forecasting Aluminium Prices: GARCH, Jumps, and Mean-Reversion". http://www.green.ecn.ulaval.ca/chaire/2005/2005-5.pdf

Bracker K. and Smith K.L. (1999), "Detecting and modelling changing volatility in the copper futures market", *Journal of Futures markets*, 19, 79-100

Bollerslev T. (1986), "Generalized Autoregressive Conditional Heteroskedasticity". *Journal of Econometrics* 31, 307-327.

Bollerslev T. (1990), "Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH approach". *Review of Economics and Statistics* 72, 498–505

Brunetti and Gilbert C.L. (1995), "Metals price volatility", *Resources policy*, 21, 237-254.

Brunetti C and Gilbert C.L. (1996), "Are metal's prices becoming more volatile?", *Proceedings of the Mineral Economics and Management Society*, 58-72.

Bulut B (2010), *Forecasting the prices of non-ferrous metals with GARCH models & volatility spillover from world oil market to non-ferrous metal markets.* Thesis submitted to the graduate school of social sciences of Middle East Technical University in partial fulfillment of the requirements for the degree of master of business administration.

Chan F., Lim C. and McAleer M. (2005), "Modelling multivariate international tourism demand and volatility". *Tourism Management*, 26, 459–471

Chen M H., (2010) "Understanding world metals prices—Returns, volatility and diversification" Resources *Policy*, 35: 127–140.

Clark P.K. (1973), "A Subordinated stochastic process model with finite variances for speculative prices". *Econometrica,* 41, 135–155.

Cheung Y-W and Ng L..K. (1996), "A Causality-in-Variance Test and its Application to Financial Market prices", *Journal of Econometrics* n° 72, pp. 33-48.

Cochran S. J. Mansur I. Odusami B. (2012), "Volatility persistence in metal returns: A FIGARCH approach", *Journal of Economics and Business*, 64 (2012), 287-305.

Engle R.F. (1982) "Autoregressive Conditional Heteroscedasticity with estimates of the variance of United Kingdom inflation*". Econometrica* 50, 987–1007.

Hammoudeh S., Yuan, Y., McAleer, M. (2009), "Shock and volatility spillovers among equity sectors of the Gulf Arab stock Markets". *Quarterly Review of Economics and Finance* 49, 829-842

John T.C. and Jerrett D. (2008), "Super Cycles in Real Metals Prices?", *IMF Staff Papers,* Vol. 55, No. 4.

Labys, W.C., A. Achouch, and M. Terraza, 1999, ‘‘Metal Prices and the Business Cycle,’’ *Resources Policy*, Vol. 25, No. 4, pp. 229–38.

Li X. and Zhang B. (2008), “Price Linkages between Chinese and World Copper Futures Markets”, *Frontiers of Economics in China*, Vol.3 No.3, pp. 451-461.

Li X. and Zhang B. (2009) “Price discovery for copper futures in informationally linked markets”, *Applied Economics Letters*, Vol. 16 Issue 15, 1555-1558.

Ling S., McAleer, M. (2003), ”Asymptotic theory for a vector ARMA-GARCH model.” *Econometric Theory* 19, 278–308.

McMillan D. and Speight A. (2001), “Non-ferrous metals price volatility: A component Analysis”, Resources Policy, Vol. 27, pp. 199-207.

McDermott, J.C., P.A. Cashin, and A. Scott, 1999, ‘”The Myth of Co-Moving Commodity Prices,’’ Bank of New Zealand Discussion Paper G99/9, Wellington, New Zealand.

Morales, L.: Volatility spillovers on precious metals markets: the effects of the Asian crisis. *Proceedings of the European Applied Business Research Conference (EABR)*, Salzburg, Austria, 23rd.-25th. June, 2008.

Peng D. Wang J. and Rao Y. (2013), “Applications of nonferrous metal price volatility to prediction of China’s stock market”, *Transactions of Non-ferrous Metals Society of China* 24(2014) 597–604

Pindyck, R.S. and Rotemberg J..J. (1990), ‘‘The Excess Co-Movement of Commodity Prices,’’ The Economic Journal, Vol. 100, pp. 1173–89.

Ross S.A. (1983), “Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy”. *Journal of Finance* 45, 1–17.

Sinha P and Mathur K (2013), “Price, Return and Volatility Linkages of Base Metal Futures traded in India”, http://mpra.ub.uni-muenchen.de/47864/

Tauchen G.E. and Pitts M. (1983), “The price variability–volume relationship on speculative markets”. *Econometrica* 51, 485–505.

Todorova N, Worthington A and Souček M. (2014), Realized volatility spillovers in the non-ferrous metal futures market *Resources Policy*, *Volume 39*, *March 2014*, *Pages 21-31.*

Watkins C. and McAleer M. (2003), “Pricing of Non-ferrous Metals Futures on the London Metal Exchange”, *Applied Financial Economics*, 2003, pages 1-51.

Watkins C. and McAleer M. (2006), “Pricing non-ferrous metals futures on the London Metal Exchange”, *Applied Financial Economics*, 2006, vol. 16, pages 853-880.

ANNEX

Annex 1: ARCH-tests

1.1 Ljung-Box test

The Ljung-Box test checks whether the data are autocorrelated based on a number of lags, m. We want to test whether the autocorrelations, $\gamma_1, \gamma_2, \ldots, \gamma_m$ of y_t is 0 or not.

The test can be defined as:

H_0: $\gamma_1=\gamma_2=\ldots=\gamma_m=0$
H_1: At least one $\gamma_i \neq 0$, $i=1,\ldots\ldots,=m$

The test statistic is:

$$Q_m = n(n+2)\sum_{i=1}^{m}\frac{\hat{\rho}_i^2}{n-i}$$

Where n is the sample size, $\hat{\rho}_i$ is the sample correlation of y_t^2 at lag, and m is the number of lags being tested. When n is large, then Q_m is asymptotically distributed as a chi-squared distribution with m degrees of freedom under the null hypothesis. Then for a significance level α, we reject H_0 if :

$$Q_m \succ \kappa^2_{1-\alpha,m}$$

Where $\kappa^2_{1-\alpha,m}$ is the α-quantile of the chi-square distribution with m degrees of freedom.

If we accept H_0, we do not reject the hypothesis that the errors are random. In practice, the selection of the number of lags, m, may affect the performance of Q_m. Therefore several values of m are often tested.

1.2 Lagrange test

The Ljung-Box test checks whether the data are autocorrelated based on a number of lags, m. We want to test whether the autocorrelations, $\gamma_1, \gamma_2, \ldots, \gamma_m$ of y_t is 0 or not.

The test can be defined as:

H_0: $\gamma_1=\gamma_2=\ldots=\gamma_m=0$
H_1: At least one $\gamma_i \neq 0$, $i=1,\ldots\ldots,=m$

The test statistic is:

$$LM_m = TR^2$$

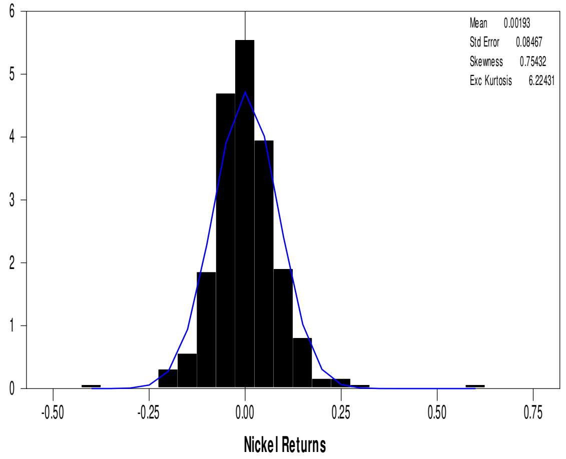
Where R^2 is the coefficient of determination of regression : $\hat{\varepsilon}_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \hat{\varepsilon}_{t\ i}^2 + \nu_t$,

ε_t are residuals from : $\ln r_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j r_{t-j} + \varepsilon_t$, r_{t_t} , are metal log returns and m is the number of lags being tested. LM_m is asymptotically distributed as a chi-squared distribution with m degrees of freedom under the null hypothesis. Then for a significance level α, we reject H_0 if :

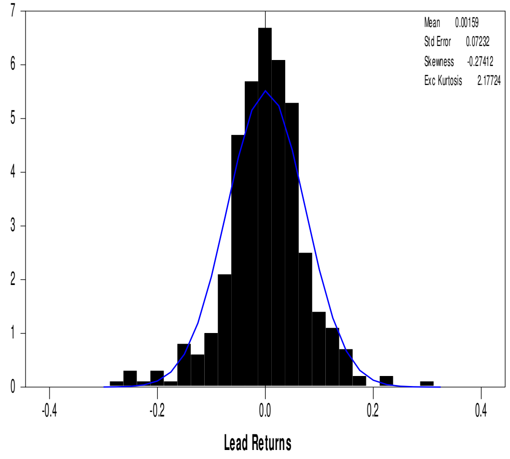
$$LM_m \succ \kappa_{1-\alpha,m}^2$$

Where $\kappa_{1-\alpha,m}^2$ is the α-quantile of the chi-square distribution with m degrees of freedom. Conclusions are same as for Ljung-Box test.

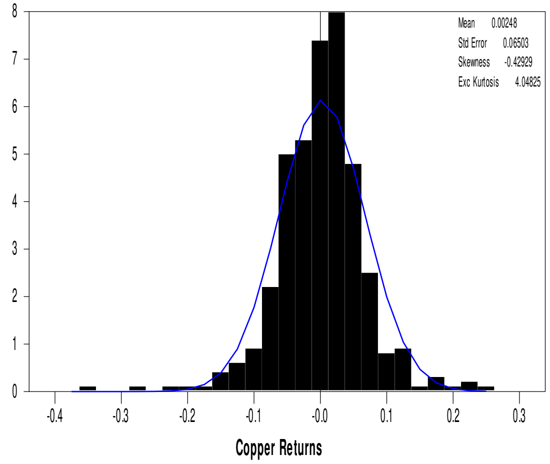
Annex 2: Histograms of log-returns



NICKEL



LEAD



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