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On the optimal dynamic hedging with nonferrous metals

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ABSTRACT

This paper employs multivariate GARCH to model conditional correlations and to examine volatility spillovers and hedging possibilities with nonferrous metals traded on the London Metal Exchange (LME) market. Three different multivariate GARCH models (diagonal, CCC and DCC) are employed and contrasted. The nonferrous metals studied are copper, aluminum, tin, lead, zinc and nickel and span the period from January 6, 2000 to February 29, 2016. The multivariate DCC GARCH framework is found to fit the data in an appropriate design and provides results showing the strongest evidence of long-term persistence volatility spillovers between lead and aluminum. We also find that the Hurst exponents given by the R/S method are on average 0.94, indicating the existence of a strong degree of long-range dependence in conditional volatilities. On average, the cheapest hedge is a long position in lead and a short position in nickel. The most expensive hedge is long nickel and short copper.

1. Introduction and Objectives

The purpose of this study is to examine correlations, volatility spillovers and hedging possibilities with nonferrous metals (NFMs) traded on the London Metal Exchange (LME) market. The metals studied are copper, aluminum, tin, lead, zinc and nickel and cover the period from January 6, 2000 to February 29, 2016. The LME has been the world center of base metals trading since its establishment in 1877. The LME is used worldwide by manufacturers and buyers of nonferrous metals as a hub for spot and futures contracts trading in these materials (McAleer and Watkins [1]) despite increased competition from the Commodity Exchange (COMEX) in the US and the Shanghai Futures Exchange (SHFE) in China, the LME remains the most liquid venue for the trading of base metals.

This investigation is important for several reasons. First, unlike precious metals such as gold and silver, which are often purchased for investment rather than commercial use, base metals are mostly notable for their industrial use. Therefore, the NFM market is among the most important world markets today. NFMs present an advantage compared to ferrous metals such as steel and cast iron since they are nonmagnetic and more resilient; many NFMs are good electrical conductors. These interesting physical properties make NFMs strategic in a variety of industrial sectors such as chemical processing, electronics, construction, jewelry, lighting, medical equipment, fiber optics transmission, solar energy and many more. Second, analyzing volatility, correlations and spillovers among nonferrous metals can be useful to market regulators concerned with commodity market volatility. Furthermore, this study may also be useful to investors and traders in developing optimal hedging strategies across these mar-

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kets.

The rest of the paper is structured as follows: the relevant literature is briefly reviewed in Section 2; Section 3 presents the econometric approach used in this study; Section 4 presents and discusses the empirical estimates and Section 5 concludes the study.

2. A Brief Review of the Literature Related to Nonferrous Metals Markets

There is a vast empirical literature analyzing microstructure of spot and futures markets for nonferrous metals. The major part of these studies relies on the LME. Nonferrous metals markets, including those for aluminum, aluminum alloy, copper, lead, nickel, tin and zinc, are frequently the subject of empirical analysis. Empirical research on spot and futures markets for nonferrous metals can be organized into four categories (Watkins and McAleer [2]): the theory of storage and cost-of-carry mode; price volatility and risk; market efficiency; and aspects of international studies on metals markets.

Implications of the theory of storage are tested in empirical studies using models of the cost-of-carry relationship and the convenience yield on holding inventories. Fama and French [3] propose a refinement to the Samuelson hypothesis. In conditions of scarcity, spot prices will increase as purchasers bid whatever is necessary to secure supply. The effect will be less pronounced in longer term futures, since agents know that higher prices will boost supply on the long run and rebuild inventory. Not only will spot prices be elevated, but they will also experience elevated volatility, so that the Samuelson hypothesis holds. Indeed, in a tight market, any news related to short-term supply, demand or inventory will have an important impact on the spot market When inventory is high, spot and futures prices have approximately the same variability (that is the Samuelson hypothesis does not hold), because the marginal convenience yield on inventory declines at higher inventory levels (but at a decreasing rate). Their empirical analysis supports their refinement of the Samuelson hypothesis.

Empirical studies dealing with price volatility and risk in NFMs markets include modelling the volatility of spot and futures prices using a random walk framework, or various GARCH models while the examination of the risk/return relationship in futures markets using a Capital Asset Pricing Model (CAPM) approach volatility of six LME spot markets has been conducted by Brunetti and Gilbert [4], and modelled through a FIGARCH process by Brunetti and Gilbert [5]. The empirical estimates suggest that the NFMs have similar volatility dynamics.

COMEX copper futures' price volatility is examined by Bracker and Smith [6] using several GARCH specifications. The authors have documented that GARCH and EGARCH models are superior to the GRJ-GARCH, the AGARCH and a random walk model. Both AGARCH and GRJ-GARCH specifications allow asymmetric effects. Negative shocks have a greater effect on the conditional variance than positive shocks.

McMillan and Speight [7] analyze the time-varying volatility of daily nonferrous prices over the 1972-1995 period. Their investigation provides a decomposition of volatility into its long-run and short-run components. The main conclusions estimates reveal relevant and significant of the decomposition of metals price volatility and the presence of three separate principal components driving underlying metals volatility.

Watkins and McAleer [2] analyze futures contracts for several NFMs, including aluminum, aluminum alloy, copper, lead, nickel, tin and zinc. Using, various long-run models, they find that there is a statistically significant long-run relationship among the futures price, spot price, stock level and interest rate.

Cochran et al. [8] examine the returns and the long-memory properties of the return volatilities for copper, gold, platinum and silver. Daily returns for the January 4, 1999 to March 10, 2009 period are used. Three main issues are investigated:

(1) whether the volatility processes present long-run dependence;

(2) whether the returns and conditional volatility of returns are affected by the uncertainty caused by the 2008 global financial crisis;

(3) whether the implied volatility in the equity market, as measured by VIX, explains a high share of metal risk and return. The results show that VIX makes a significant contribution to forecast metal returns and return volatility. The empirical estimates also suggest that events during the global turmoil contribute to increase return volatility for most metals.

Concerning efficiency, several papers examine metal markets for common stochastic trends, equilibrium parity relationships between markets and lead-lag relationships between markets. Franses and Kofman [9] test for flow parity relationships between forward prices for aluminum, copper, lead, nickel and zinc on the LME. They find that a cointegrating relationship exists between the five industrial metals, so that a long-run relationship exists between the forward price series. If efficiency is defined such that a random walk is the best forecasting scheme, the LME is inefficient. Similarly, Agbeyegbe [10] tests for common stochastic trends among copper, lead and zinc spot prices

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on the LME and finds one relationship between the three metals and a bivariate relationship between copper and lead. However, in both Franses and Kofman [9] and Agbeyegbe [10], the authors do not interpret cointegration as evidence of inefficiency.

Todorova et al. [11] employ a multivariate heterogeneous autoregressive (HAR) model to examine the volatility spillovers among five of the most liquid and important nonferrous metals contracts (aluminum, copper, lead, nickel and zinc) traded on the LME using intraday data over the period of June 2006 to December 2012. Their empirical estimates show that the volatility series of other base metals comprise valuable information for future price volatility. However, their own dynamics are often enough for describing most future daily and weekly volatilities, with the most pronounced volatility spillovers identified in the longer term.

Studies based on international linkages between markets are more and more developed. Shyy and Butcher [12] examine the dynamic links between the SHME, operating under strict Chinese Government controls, and the LME. They find that spot and forward prices for copper on the SHME are cointegrated with the respective copper spot and forward prices on the LME, and it is claimed that the SHME prices coincide with those of the world market Trading on the SHME starts well before that of the LME, and one would expect that, if the SHME is important with respect to world metal prices, information from the SHME trade would be accommodated by participants in the LME exchange.

An extensive body of the literature has studied copper futures markets in an international approach. Li and Zhang [13] investigate the time-varying relationship using rolling correlations and rolling Granger causality followed by co-integration tests. The results of co-integration tests show that there is a long-run relationship between the Shanghai Futures Exchange (SHFE) and the LME copper prices. Li and Zhang [14] also examine the relationship between copper traded on the SHFE and the LME using co-integration and the Markov Switching VECM model. They find a long-run relationship between the two copper futures markets. They also find that the influence of the LME on the SHFE is stronger than that of the SHFE on the LME.

Sinha and Mathur [15] have found strong linkages across the price, return and volatility of futures contracts traded on both the Indian commodity exchange and the LME for aluminum, copper, nickel, lead and zinc using a VAR-DCC-GARCH model. Yue et al. [16] explore the co-movements between Shanghai Futures Exchange (SHFE) and LME contracts. Their results suggest that LME nonferrous metals prices have a greater impact on Chinese NFMs prices. However, they find that the impact of Chinese nonferrous metals prices on LME nonferrous metals prices is low except for lead price. They also show that co-movements are time-varying, and the correlation of lead prices between LME and China is the more stable than all other NFMs prices

3. Econometric Approach

In this paper, the econometric approach employed has two components as in Sadorsky [17]. A vector autoregressive (VAR) framework with one lag is used to model the returns. A Multivariate GARCH (MGARCH) model is used to model the time-varying correlations. Three types of MGARCH are employed, namely, the Constant Conditional Correlation (CCC), the Dynamic Conditional Correlation (DCC) and the Diagonal (DIAG) models. The conditional variance is assumed to be VARMA-GARCH (1,1).

Specifically, let $r_t = \left(r_{1t}, \cdots\cdots r_{nt}\right)'$ be a (6×1) vector of NFM return at $t = 1, \ldots, T$ false. The conditional mean equation in the model is specified as a vector autoregressive process of order one. It takes the following form:

$$r_{it} = \sum_{j=1}^{6} \varphi_{ij} r_{jt-1} + \varepsilon_{it} ; \varepsilon_{it} \mid I_{t-1} \sim \aleph\left(0, h_{it}\right) \quad (1)$$

r_{1t}, r_{2t}, r_{3t}, r_{4t}, r_{5t} and r_{6t} are the copper, aluminum, tin, lead, zinc and nickel return series at t, respectively. With $\varepsilon_{it} = e_{it}\sqrt{h_{it}}$, a (6×1) vector of errors of the mean equation that are estimated conditional on the available information up to t-1 for the copper (ε_{1t}), aluminum(ε_{2t}), tin(ε_{3t}), lead(ε_{4t}), zinc(ε_{5t}) and nickel(ε_{6t}) return. $\left|\varphi_{ij}\right| < 1$ and $\left\{e_{it}\right\}$ are independently and identically distributed (i.i.d) random variables and h_{it} the conditional variances for the copper(h_{1t}), aluminum(h_{2t}), tin(h_{3t}), lead(h_{4t}), zinc(h_{5t}) and nickel(h_{6t}) return defined as:

$$h_{iit} = \theta_{ii} + \sum_{j=1}^{2} \alpha_{ij} \varepsilon_{jt-1}^{2} + \sum_{j=1}^{2} \beta_{ij} h_{jjt-1} + \gamma_i \varepsilon_{it-1}^{2} S_{it}^{-} \quad (2)$$

where S_{it}^{-} is an indicator function, in this case, for $\varepsilon < 0$. With this formulation, a positive value of γ_i means negative residuals tend to increase the variance more than positive ones. Put otherwise, negative shocks increase variance more than positive shocks do.

Equation (2) is specified a GARCH (1,1) process with VARMA terms as in Ling and McAleer [18]. This shows 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

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transmission. The presence of h_{jt-1} captures the volatility spillovers or interdependencies among the NFMs. They define GARCH effects of past volatilities and represent the contribution to the long-run persistence.

Next, the multivariate conditional covariance matrix in the DCC is expressed as follows:

$$H_t = D_t R_t D_t \quad (3)$$

where D_t is the $(n \times n)$ diagonal matrix of time-varying standard deviations from univariate GARCH with $\sqrt{h_{iit}}$ on the *i-th* diagonal $i=1,2,...,n$; R_t is the $(n \times n)$ conditional correlation matrix. The DCC model introduced by Engle [19] has a two-stair estimation of the conditional covariance matrix H_t. In the first stair, univariate volatility models are fitted for each of the metal returns and estimates of $\sqrt{h_{iit}}$ are obtained. In the second stair, return residuals are transformed by their estimated standard deviations from the first stair. That is $u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$ where u_{it} is then used to estimate the coefficients of time-varying correlation. The evolution of the correlation in the DCC model is given by:

$$Q_t = \left(1 - a - b\right)\overline{Q} + a u_{t-1} u_{t-1}^{'} + b Q_{t-1} \quad (4)$$

where $Q_t = \left(q_{ijt}\right)$ is the $(n \times n)$ time-varying covariance matrix of u_t, $\overline{Q} = E\left[u_t u_t^{'}\right]$ is the $(n \times n)$ unconditional variance matrix of u_t. a and b are non-negative scalar parameters satisfying $(a+b) < 1$. Since Q_t does not usually have ones on the diagonal, we scale it to obtain a proper correlation matrix R_t. Thus,

$$R_t = \left(diag\left(Q_t\right)\right)^{-\frac{1}{2}} Q_t \left(diag\left(Q_t\right)\right)^{-\frac{1}{2}} \quad (5)$$

R_t in (4) is a correlation matrix with ones on the diagonal and an off-diagonal element less than one in absolute value, as long as Q_t is positively definite. A typical element of R_t is of the form:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}, i, j = 1, 2, ..., n, \ \ and \ \ i \neq j \quad (6)$$

For the CCC model case, $R_t = R$ and $R_{ij} = \rho_{ij}$. The conditional covariance between metal returns is as follows:

$$\left[h_{ij}\right]_t = \boldsymbol{\rho}.\sqrt{h_{it}}.\sqrt{h_{jt}} \quad (7)$$

where ρ is the constant conditional correlation.

In the diagonal MGARCH model, $\rho_{ij}=0$ for all i and j. The diagonal case is very restrictive because it assumes that the dynamic conditional correlations between variables are all zero $h_{ij}=0 \ \forall \ i \neq j$. The standardized residuals from the MGARCH diagonal model can be employed to calculate an unconditional covariance matrix. The MGARCH models are estimated by Quasi-Maximum Likelihood Estimation (QMLE) using the simplex algorithm.

After obtaining the conditional volatility series from the DCC-GARCH model, we examine long-range dependence properties accurately by Hurst exponent H, calculated by the rescaled range analysis (R/S method) which provides interpretation of an empirical law, the Hurst law. The R/S method proposed by Hurst [20] originally demonstrates the long-range dependence via the coefficient H, which is often applied to capture the long memory property. The R/S statistics has a power-law:

$$\left(R/S\right)_T = aT^H \quad (8)$$

where T is the number of observations and a is a constant. (8) can be log-linearized as follows:

$$\log\left(R/S\right)_T = \log a + H \log T \quad (9)$$

Several implications can be derived as follows: when the series display positive long-run dependence or persistence, we obtain the Hurst exponent H between 0.5 and 1.0; on the contrary, with negative long-run dependence or anti-persistence, the exponent H is between 0 and 0.5; and when the Hurst exponent H equal to 0.5, the series then conform to the behavior type of random walk.

4. Sample Data and Preliminary Analysis

We use daily closing prices for copper, aluminum, tin, lead, zinc and nickel from January 6, 2000 to February 29, 2016. These prices are expressed in US dollars and are sourced from the Bloomberg terminal.

Figure 1 shows that NFM prices vary over time. Copper prices reached a low point by the late 2001 and did not start to reverse course until 2003, escalating to a peak by the first quarter of 2004. After reaching this intermediate peak, copper prices displayed a behavior like that observed in a typical bullish market environment. Multi-quarter copper price increases served to shed excessive greed, followed by copper prices easing right back into their upward trend. However, 2006 ushered in a period of high uncertainty. This is because fears of supply shortages emerged as China began to systematically ravage the supply of copper. And this brought a long season of extreme volatility (Figures 2 and 3).

About the other base metals, Figure 1 indicates that all metal prices behave in a similar manner. Zinc's bull also started out in orderly fashion. From its 2003 low, zinc gradually rose higher, bolstered by multi-year support, gaining an impressive increase in the first half of 2005. Nickel's uptrend indeed exhibited multi-year support leading into 2006, but its swings are much more violent.

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Nickel got out to a much faster start than the other base metals. Its late 2003 parabolic surge gave it an early bull gain. But the rise was only beginning. From its 2005 low nickel took flight in near-linear ascent, driving it to record highs. Not deviating from the greater NFMs theme, lead's bull market also started out with an orderly uptrend lead by multi-year support. Entering 2006, however, lead fell behind the pack and jumped the base metals trend. While the other base metals prices continued to rise, lead prices were falling hard.

Measured by volume, aluminum has the largest market of the nonferrous metals. More aluminum is mined and consumed each year than the four metals above combined. And it is because of this larger market that volatility is not as extreme (Figure 3). In fact, compared to the others, aluminum's price has been less volatile until recently. Visually, aluminum paints a similar picture to the other base metals. Its strong initial upsurge and the velocity of its gains appear to be in line with the other metals. After a bit of a pullback in mid-2005, aluminum then set course for its version of an impressive upsurge. After aluminum achieved its 2006 apex, an all-time high, it then spent the next 2 years without a significant change.

Figure 1 also shows that the recession of 2008-2009 had a big negative impact on the NFM prices. With the 2008 global financial crisis, a drastic shift in base metals fundamentals has been quick to collapse copper. With demand growth quickly slowing and then jumping to declining, supply rapidly caught up and the supply-deficient imbalance all but disappeared. Zinc's decline accelerated into 2008 as suppliers were able to meet demand and LME stockpile levels have impressively risen since the beginning of 2008. With the imbalance swinging to supply, surplus zinc was already during a healthy correction by the time the stock panic hit. But the stock panic was quick to add to the pain, driving zinc to levels not seen since 2004.

Rounding the corner into 2008, nickel settled into a sideways consolidation, but a further rise in stockpile levels caused nickel to break through support and continue its decline. The stock markets near collapse lead to a significant cut in the price of nickel. In fact, nickel prices dropped nearly in half yet again before finally bottoming in October at levels not seen since 2004.

It is impossible to use data directly extracted from the Bloomberg database as mean, variance and autocorrelation structures change over time. Therefore, in order to ensure stationarity, copper, aluminum, tin, lead, zinc and nickel returns are defined as continuously compounded or log returns (Figure 2) at time t, γ_t, calculated as follows:

$$\gamma_t = 100 \times \log\left(\frac{P_t}{P_{t-1}}\right) = 100 \times \left[\log\left(P_t\right) - \log\left(P_{t-1}\right)\right] \quad (10)$$

where P_t and P_{t-1} are metal prices for days t and $t-1$, respectively.

Figure 2 depicts the daily movements of metals returns from January 6, 2000 to February 29, 2016. Notice that volatility clustering can be easily observed. Large changes follow large changes of either sign and small changes follow small changes.

Time series graphs of the squared daily returns show how volatility has changed across time. There appear to be strong linkages in volatility across NFM, as evidenced by pronounced volatility clustering between September 2007 and August 2009. Moreover, Figure 3 shows big spikes in volatility in March 2004, October and November 2006.

Descriptive statistics are reported in Table 1. Only the sample mean of aluminum is negative. The characteristics of log-returns series used in our data set 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 the excess kurtosis coefficient of the data which indicates that metal returns are leptokurtic relative to normal distribution. All metals report negative skewness. Therefore, the dataset deals with 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.

Before we conduct the GARCH tests, we test for the existence of ARCH effects in the data sets. The results are shown in Panel B, Table 1 and display clear evidence of significant ARCH effects in all metal prices. The Ljung-Box statistic for 22 lags applied on returns indicates that significant linear dependencies exist. Furthermore, the Engle [21] ARCH-LM 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 the one per cent level, implying that there exist significant ARCH effects in the data at all frequencies.

Unconditional correlations suggest that there is positive correlation between daily returns of NFM traded on the LME (Panel A, Table 2). Specifically, copper has strong correlation with aluminum, lead and zinc: 0.70488, 0.63052 and 0.73344, respectively. Zinc also has significant correlation with aluminum and lead, respectively, 0.65739 and 0.66165.

The correlations between the squared daily returns also show positive correlation among NFM. The information provided in Figure 3 and Panel B, Table 2 shows volatility clustering and cross-correlations in volatility, respectively. But it is worth noting that cross-correlation is more accurate between zinc and copper.

5. Empirical Results and Discussion

This section reports on the empirical results obtained from estimating multivariate GARCH models in Tables 3-8. The DCC model is used as the benchmark and is then compared to other restricted correlations models (DIAG and CC), estimated with a student distribution of errors and asymmetric shocks justified by Table 1.

5.1. Regression Results

5.1.1 Past Returns Determine Current Returns

Turning first to the return-generating process, only past values of lead returns (φ_{44}) determine significantly their current values in all models (Panel A, Table 6). The DCC model provides the most important correlation $(\varphi_{44} = 0.083)$. This influence suggests that past returns can be used to forecast future returns for lead, implying short-term predictability for lead price changes.

In terms of information transmission through returns, aluminum negatively affects current copper, lead, zinc and nickel returns. The estimated coefficient of aluminum in the copper (φ_{12}), lead (φ_{42}), zinc (φ_{52}) and nickel (φ_{62}) equations are negative, of the same order of magnitude in all the models (on average 0.07 for copper, 0.09 for lead, 0.04 for zinc and 0.09 for nickel) and statistically significant at the 1% level for each of the MGARCH models (Panel A, Tables 3, 6, 7 and 8). This result is important in establishing a negative relationship between aluminum and those metals. The highest metal reactions to a price change are observed for lead and zinc. As shown in Panel A, Table 6, a 1% variation in the price of aluminum causes an 8.2% decrease in the price of Lead, implying that information flows mostly from the aluminum market to the lead market and not the other way around. At the same time, past values of copper and zinc returns (φ_{21} and φ_{25} respectively) negatively affect current aluminum returns (Panel A, Table 4).

Furthermore, one period lag of nickel and lead positively affects current tin (Panel A, Table 5) and nickel (Panel A, Table 8), respectively in all MGARCH models. This result is important in establishing a positive relationship between current period tin and nickel returns and last period nickel and lead returns, respectively. In other words, current period tin and nickel returns are influenced by last period nickel and lead returns, respectively.

5.1.2 Significant Long-range Dependence in Volatility Exists on the NFM Spot Market

Turning to the conditional variance equations, the estimated results of the GARCH coefficients (β_{ii}) are significant at conventional levels in all the NFM (Panel B.2, Tables 3-8). Sensitivity to their past conditional volatility (h_{it-1}) appears to be significant for the NFM prices, implying that past variance returns increase current volatility of NFM returns. The zinc volatility is the most sensitive in the DCC-MGARCH model ($\beta_{55} = 0.938$, Panel B.2, Table 7), followed by the copper ($\beta_{11} = 0.886$, Panel B.1, Table 3), while the aluminum return is at the tail end of the volatility ranking ($\beta_{22} = 0.482$, Panel B.2, Table 4). This finding suggests that the 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.

Own conditional ARCH effects, which measure short-term persistence, are important in explaining the conditional volatility (Panel B.1, Tables 3-8). For each NFM, the estimated (α_{ii}) values for ARCH effects are smaller than their respective estimated GARCH effects values (β_{ii}), indicating that own volatility long-run (GARCH) persistence is larger than short-run (ARCH) persistence. The NFM market's former volatilities are more important in predicting future volatility than past shocks.

In Figure 4, we illustrate the volatility series of estimated results of Hurst exponents using the R/S method. We find that the Hurst exponents by the R/S method are on average 0.94, indicating the existence of strong degree of long-range dependence in conditional volatilities. All NFM display the long memory property and the type of the long memory is positive, i.e., persistence in volatility.

5.1.3 Bad and Good News Have Dissymmetric Effects on Copper Volatilities

Furthermore, return variances for copper exhibit significant asymmetry in all multivariate GARCH specifications. In the DCC Benchmark model, the coefficient of sensitivity to negative information ($\alpha_{ii} + \gamma_i$, cf. (2)) is 0.081 (Panel B, Table 4); the coefficient of sensitivity to positive shocks ($\alpha_{ii} - \gamma_i$, cf. (2)) is 0.028. This finding suggests that copper reacts more actively to negative shocks as stocks market.

5.1.4 Spillover Effects between Nonferrous Metals

Results in Panel B, Tables 3-8 on volatility interdependence show significant volatility spillovers between metal returns.

For the DCC model there are several instances of significant volatility spillovers. For short-term persistence there is evidence of negative volatility spillovers be-

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tween tin and aluminum (α_{23}) (Panel B.1, Table 4) and between aluminum and tin (α_{32}) (Panel B.1, Table 5) Results in Tables 3 and 8 also show how past news from copper affects the volatility behavior of nickel (α_{61}) and vice versa (α_{16}), with estimated coefficients of 0.095 and -0.011, respectively. Significant spillovers exist across the nickel and copper returns. This result is in line with Todorova et al. [11] who find that the short-term realized volatilities of nickel are significant for copper. However, in our results, it appears that the absolute value of α_{61} is greater than α_{16}, implying that the spillovers from copper to nickel are more significant than the reverse direction, which means that the information flow from copper to nickel is stronger. Furthermore, there is significant short-term persistence volatility spillover which is negative from aluminum to copper (α_{12}) (Panel B.1, Table 3); negative from tin to nickel (α_{63}) (Panel B.1, Table 8); negative from lead to nickel (α_{64}) (Panel B.1, Table 8); and, positive from nickel to aluminum (α_{26}) (Panel B.1, Table 4).

There is also evidence of long-term persistence volatility spillovers in the DCC model. There is significant inter-sector or volatility spillover effects from copper to aluminum (β_{21}) and lead (β_{41}). But the transmission is more important to lead $(\beta_{41} = -0.303)$ than to aluminum $(\beta_{21} = -0.209)$. The DCC model also presents evidence of a statistically significant long-term persistence volatility spillover from aluminum to copper (β_{12}), tin (β_{32}), lead (β_{42}) and nickel (β_{62}) (Panel B.1, Tables 3, 5, 6 and 8). Since copper, aluminum and lead are produced in the same geographic area, they are affected by the same environmental events. Indeed, the leading 3 producers of aluminum (Australia, Brazil and China) account for more than 50% of worldwide production; the leading 3 producers of copper (Chile, the United States and Indonesia) account for about 50% of world production; and the leading 2 producers of lead (China and Australia) accounted for about 50% of world production.

The spillover emerging from aluminum volatility to the long-term price variation of nickel spot may be ascribed, for example, to the relevance of both metals for the automobile industry, which is also the major application area for nickel (Todorova et al. [11]).

The tin conditional volatility also seems to add significant information to the forecasts of copper (β_{13}), aluminum (β_{23}), lead (β_{43}) and nickel (β_{53}) (Panel B.2, Table 3, 4, 5, and 6). Lead conditional volatility has significant effects on aluminum (β_{24}) and nickel (β_{64}) (Panel B.2, Tables 4 and 8) while there is spillover effect between zinc and the other NFM (Panel B, Tables 3-8). The construction of infrastructure could be the source of the spillover from the zinc to the aluminum and copper spot markets, and the demand for copper and lead to produce electronic and electrical components can explain the volatility transmission of copper to lead (β_{41} =-0.303).

The results for variance equation of copper, aluminum, lead and zinc, with the DCC model, reveal that nickel is a significant source of the long-term persistence volatility spillovers, with corresponding coefficients estimates $\beta_{16} = 0.033$, $\beta_{26} = 0.176$, $\beta_{46} = 0.118$ and $_{56}$ 0.055 (Panel B.2, Table 3-8 except 5).

As shown in Panels B.3, Tables 3-8, the estimates for constant conditional correlations (CCC) between the metal returns are all positive and statistically significant at the 1% level. However, the estimates demonstrate that the highest CCC is between copper and zinc, suggesting more mutual responses to economic factors among these metals than the other metals.

Both the AIC and SBC criteria show that the DCC model is the best model. The diagnostic Ljung-Box statistics tests for the standardized residuals and standardized residuals squared show no evidence of serial correlation at the 1% level in the DCC model (Table 9). Based on the AIC, SBC and residual diagnostic tests, the DCC model is chosen as the best of the models considered. Thus, the DCC model will be used to construct dynamic conditional correlations, optimal hedge ratios and portfolio weights.

5.2. Dynamic Conditional Correlations

Figure 4 depicts pair-wise conditional-correlation coefficients between NFM traded on LME namely copper, aluminum, lead, tin, zinc and nickel. The dynamic conditional correlations can vary a lot from the constant conditional correlations ($\rho_{21} = 0.71$, $\rho_{31} = 0.45$, $_{32}$ 0.42, $\rho_{41} = 0.63$, $\rho_{42} = 0.56$, $\rho_{43} = 0.39$, $\rho_{51} = 0.71$, $\rho_{52} = 0.65$, $\rho_{53} = 0.42$, $\rho_{54} = 0.68$, $\rho_{61} = 0.56$, $\rho_{62} = 0.49$, $\rho_{63} = 0.40$, $\rho_{64} = 0.55$ and $\rho_{65} = 0.55$) emphasizing the opportunity to compute dynamic conditional correlations.

These time-series patterns show that the pair-wise conditional correlations clearly increased during the 2008 global financial crisis. The stock panic brought by the 2008 crisis wreaked havoc on virtually every securities class, and nonferrous metals were not safe to the harmful effects. Already within corrective environments, the global panic has bled the NFMs to dangerously unhealthy levels. These losses have been devastating for investors and agents holding positions in industrial metals related. These sharp deteriorations have lopped off not only the speculative premiums but many years' worth of gains for each of the major metals. The global stock panic has birthed what is turning out to be a nasty recession. And a swift contraction of global economic activity has rapidly altered base metals fundamentals. Demand has fallen drastically and suddenly so that many of the base metals have supply surpluses. Another explanation can be the fact that in the depression period a high share of the world's metals demand came from America's industrial machine. And consequently, most of the market makers were American.

Notice that the dynamic conditional correlations between the NFM are all positive and generally larger than 0.25. This indicates that there is little scope for portfolio between these metals on the LME. This is true especially between lead and zinc, aluminum and zinc, copper and zinc, and, copper and aluminum. The time series plots in Figure 5 show that, for each pair of series, the dynamic conditional correlations provide much more useful information than do the correlations from the constant conditional correlations model. It is also worth noting that at the onset and duration of the recession of 2008 and 2009, due to the global financial crisis, the dynamic conditional correlations were, for each pair of series, much larger than their corresponding values from the constant conditional correlations, illustrating that any calculations done with the correlations from the CCC model would have been very misleading.

5.3. Dynamic Hedging and Portfolio Diversification

As suggested by Kroner and Sultan [22], the conditional volatility estimates may be used to construct hedge ratios. A long position in one asset i can be hedged with a short position in a second asset j. The hedge ratio between asset i and asset j is

$$HEDGES(i,j)_t = {h_{ijt}}/{h_{jjt}} \qquad (11)$$

The time-varying volatilities from MGARCH models can also be employed to construct optimal portfolio weights (Kroner and Ng [23]).

$$w_{ijt} = \frac{h_{jjt} - h_{ijt}}{h_{iit} - 2h_{ijt} + h_{jjt}} \qquad (12)$$

$$w_{ijt} = \begin{cases} 0, if\, w_{ijt} < 0 \\ w_{ijt}, if\, 0 \leq w_{ijt} \leq 1 \\ 1, if\, w_{ijt} > 1 \end{cases}$$

By construction, w_{ijt} is the weight of the first asset in a one-dollar portfolio of two assets i and j at time t. h_{ijt} is the conditional covariance between i and j while h_{jjt} is the conditional variance of asset j.

For most of the hedge ratios, computed from the DCC model, the graphs show considerable variation after September 2008 (Figure 6). The average value of the hedge ratio between copper and aluminum (HEDGES (1, 2)) is 0.819 while the average value of the hedge ratio between nickel and aluminum (HEDGES (6,2)) is 0.862331 (Table 9). These results are important in establishing that a \$1 long position in copper can be hedged for 86.5 cents with a short position in the aluminum on the LME. A \$1 long position in nickel can be hedged for 86.23 cents with a short position in the aluminum. The cheapest hedge is long lead and short nickel (HEDGES (3,6) =0.315438, Table 9). The most expensive hedge is long nickel and short copper (HEDGES (6,1)= 0.865242, Table 9). Notice that, overall, hedging on the LME is expensive, and that many of the hedge ratios record maximum values in excess of unity.

Summary statistics for portfolio weights computed from the DCC model are reported in Table 10. The average weight for the aluminum/copper portfolio is 0.34, indicating that for a \$1 portfolio, 34 cents should be invested in aluminum and 64 cents invested in copper (Table 10). The average weight for the nickel/aluminum portfolio, which is the highest, indicates that 90 cents should be invested in nickel and 10 cents invested in aluminum (Table 10).

6. Summary and Concluding Comments

As the amount of money invested in the NFM on the LME sector grows, it is important to have a better understanding of the volatility dynamics of those metals' prices. This paper employs multivariate GARCH models to examine correlations, spillover effects and dynamic hedging with nonferrous metals traded on the London Metal Exchange (LME). The specific nonferrous metals studied are copper, aluminum, tin, lead, zinc and nickel.

For return and volatility spillover, results show significant transmission among the base metals. Regarding the return-generating process, past values of metal returns largely determine their current values at different levels. As for the conditional variance equations, sensitivity to their past conditional volatility appears to be significant for the metal prices, implying that past variances of returns increase current volatility of metal returns. Our findings also corroborate previous studies showing significant volatility spillovers between base metals (see, for example, Cochran et al. [7], and Todorova et al. [11]).

The findings of this study can provide useful information to market regulators and governments concerned with commodity market volatility. These findings may also be helpful to investors, traders, and portfolio managers in designing and implementing optimal and profitable hedg-

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ing strategies across the base metal markets. Furthermore, firms that use these base metals as inputs may find the results of our study useful in managing production costs and forecasting future metal return volatility. Finally, both importers and importer countries are likely to find the results in this study provide useful information in dealing with the continuing volatility in these industrially important commodity markets.

7. Supplement: Figures and Tables

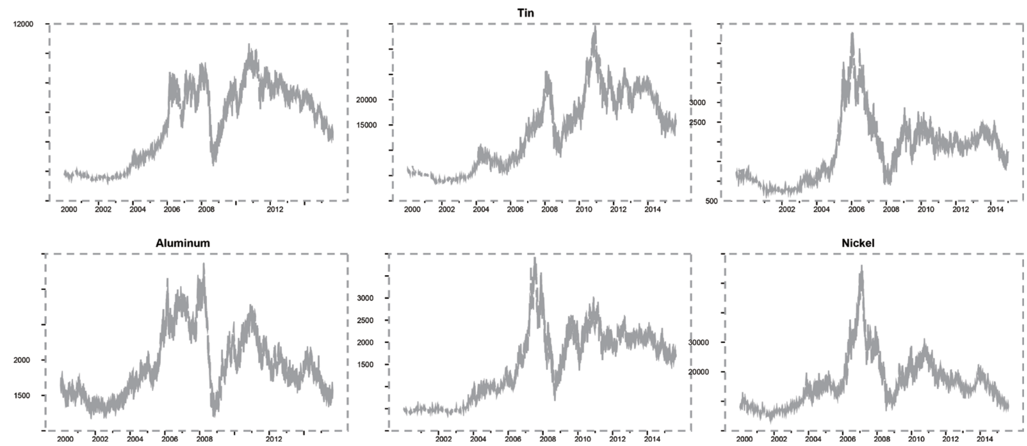

Figure 1. Metal prices

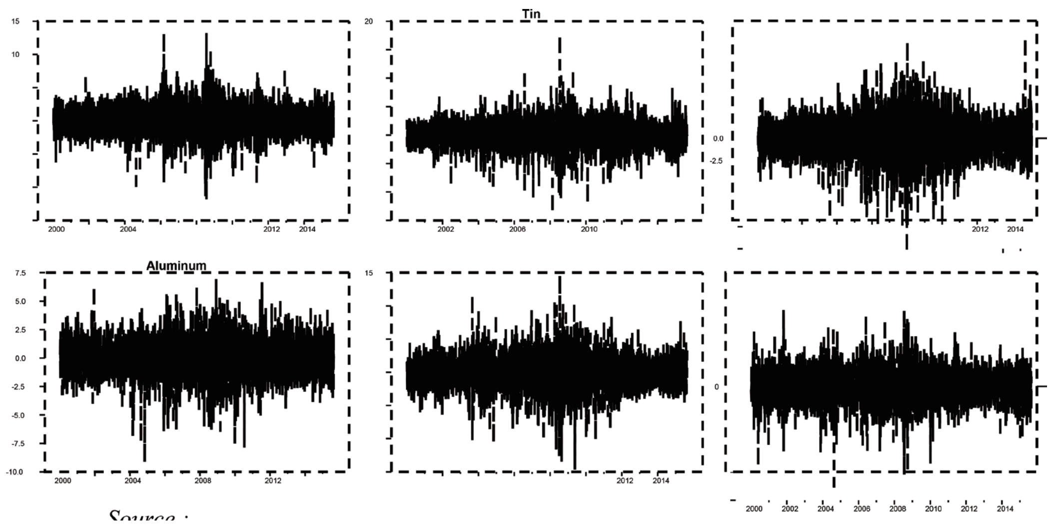

Figure 2. Daily metal returns

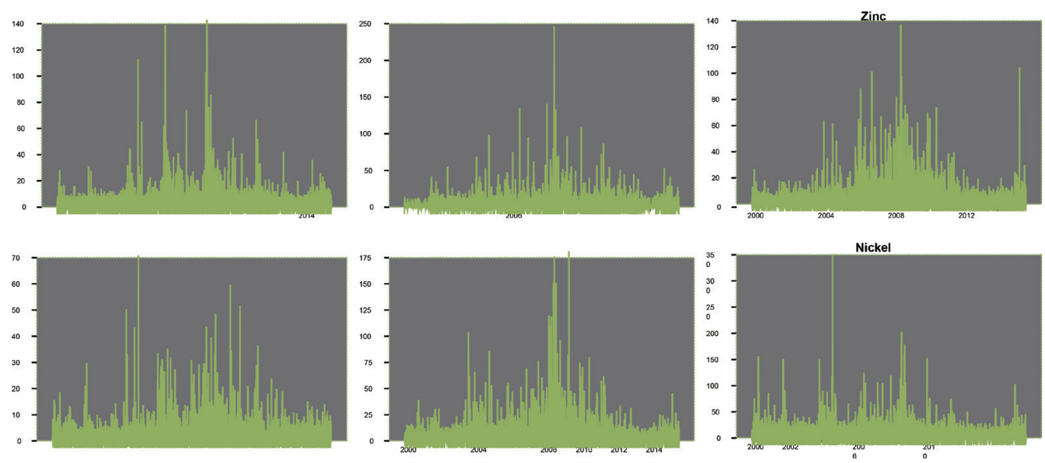

Figure 3. Squared Daily metal returns

Table 1. Summary statistics of metals returns

	Copper	Aluminum	Tin	Lead	Zinc	Nickel
	Panel A: Descriptive statistics					
Mean	0.023079	-0.000818	0.024260	0.032016	0.009220	0.000515
SD	1.741845	1.404174	1.774311	2.119674	1.920127	2.412372
Max	11.725897945	6.0679380631	15.385363542	13.007210880	9.948958270	13.309623854
Min	-10.357993718	-8.2551159064	-11.453228948	-13.199197655	-11.471979579	-18.358577947
J-B	2906.736932[a]	818.841892[a]	5923.128958[a]	1890.610441[a]	1399.617360[a]	2025.053320[a]
Kurt	4.129790 [a]	2.152561[a]	5.895960[a]	3.313242[a]	2.847890[a]	3.443193[a]
Skew	-0.118187[a]	-0.216068[a]	-0.162198[a]	-0.194839 [a]	-0.179319[a]	-0.127735[a]
ADF	-47.5032[a]	-46.6086[a]	-45.0695[a]	-44.9478[a]	-46.4039[a]	-46.6355[a]
	Panel B: Independence and ARCH Tests					
LB (22)	52.4823	26.82984	29.7844	39.6787[b]	22.8648	36.4168[b]
LB2 (22)	4111.7064 [a]	867.98196[a]	1344.6253[a]	2081.6170[a]	2342.6004[a]	1247.4697[a]
Arch-LM(8)	660.929[a]	203.213[a]	345.775[a]	442.931[a]	401.762[a]	356.861[a]

Note: c, b and a denote significance levels of 10%, 5% and 1%, respectively. SD denotes standard deviation; J-B is the Jarque-Bera; LB(8) and LB2(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); Source: Bloomberg, Authors regressions.

Table 2. Correlations between NFM

	Copper	Aluminum	Tin	Lead	Zinc	Nickel
	Panel A: Unconditional correlations between daily returns					
Copper	1					
Aluminum	0.70488	1				
Tin	0.50908	0.43745	1			
Lead	0.63052	0.54804	0.4436	1		
Zinc	0.73344	0.65739	0.46523	0.66165	1	
Nickel	0.59586	0.51935	0.43721	0.49233	0.55519	1
	Panel B: Unconditional correlations between squared daily returns					
Copper	1					
Aluminum	0.52155	1				
Tin	0.32058	0.22115	1			
Lead	0.39979	0.33597	0.23315	1		
Zinc	0.57571	0.46517	0.25792	0.46228	1	
Nickel	0.48396	0.29203	0.26705	0.28670	0.39323	1

Source: Bloomberg, Authors calculations

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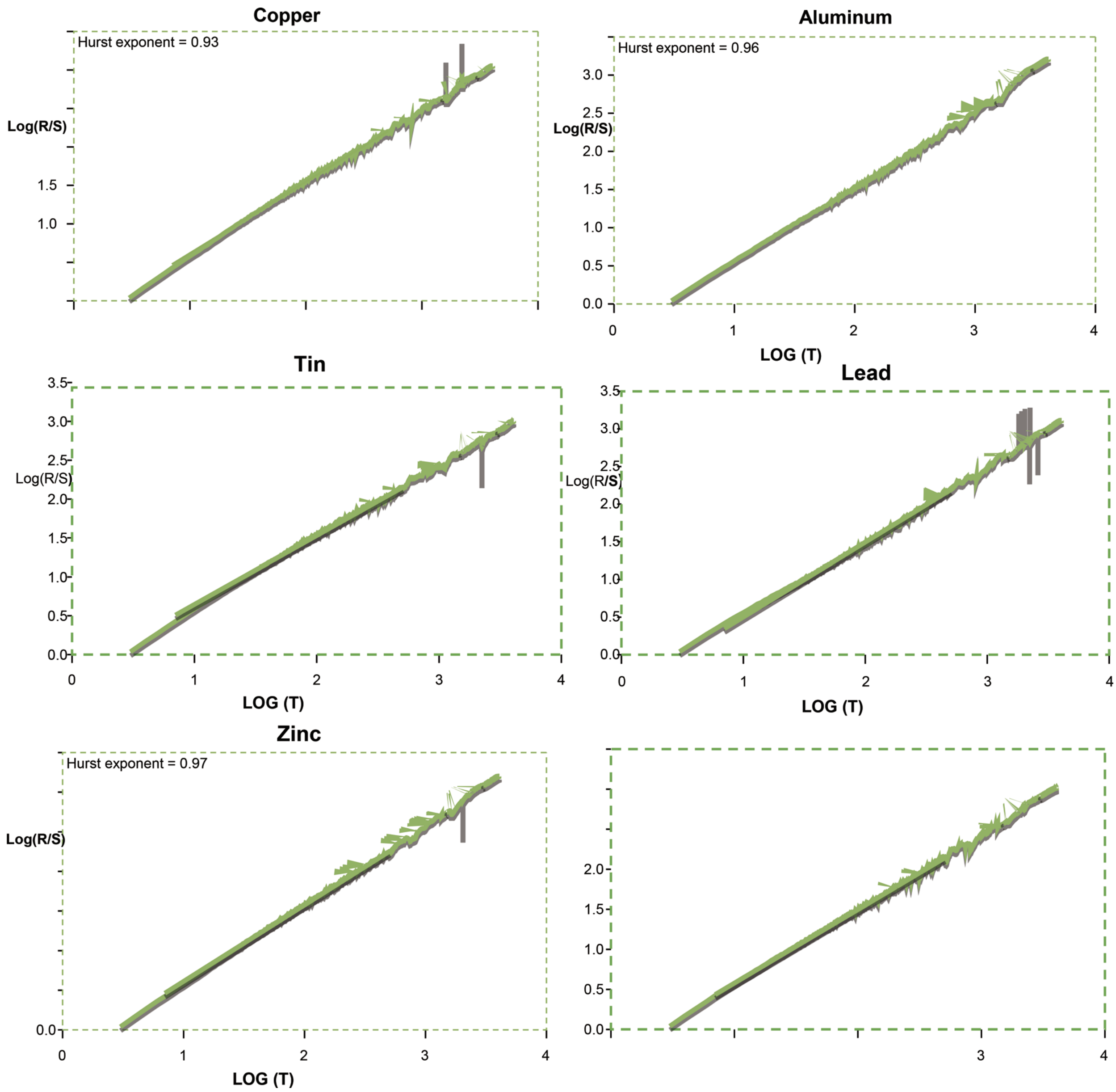

Figure 4. Results of long memory for DCC conditional volatility series

Table 3. MGARCH parameter estimates - Copper -

Coeff		Diagonal			CCC			DCC		
		Std. Error	P-value	Coeff	Std. Error	P-value	Coeff	Std. Error	P-value	
		Panel A: Mean equation								
Copper(-1)	11	-0.019	0.013	0.132	-0.005	0.013	0.712	0.010	0.007	0.132
Aluminum(-1)	φ_{12}	-0.077	0.014	0.000	-0.101	0.015	0.000	-0.070	0.009	0.000
Tin(-1)	φ_{13}	-0.004	0.012	0.755	-0.001	0.012	0.881	-0.002	0.007	0.730
Lead(-1)	φ_{14}	0.002	0.010	0.873	0.001	0.010	0.919	0.050	0.006	0.414
Zinc(-1)	φ_{15}	-0.002	0.011	0.847	-0.006	0.011	0.607	-0.024	0.006	0.000
Nickel(-1)	φ_{16}	-0.016	0.008	0.047	-0.013	0.009	0.141	-0.011	0.005	0.035

		Panel B: Variance equation								
Constant	θ_1	0.050	0.013	0.000	0.120	0.047	0.011	0.098	0.011	0.000
		B.1- ARCH effects								
Copper	α_{11}	0.044	0.020	0.029	0.109	0.035	0.0011	0.052	0.014	0.000
Aluminum	α_{12}	-0.033	0.022	0.138	-0.071	0.044	0.105	-0.038	0.0150.011	0.011
Tin	α_{13}	0.001	0.015	0.928	-0.052	0.033	0.116	0.012	0.012	0.328
Lead	α_{14}	0.014	0.016	0.386	-0.055	0.030	0.065	0.002	0.009	0.832
Zinc	α_{15}	0.012	0.020	0.545	0.099	0.034	0.04	-0.001	0.012	0.933
Nickel	α_{16}	-0.006	0.012	0.601	-0.045	0.019	0.015	-0.011	0.006	0.073
		B.2- GARCH effects								
Copper	β_{11}	0.938	0.003	0.000	0.156	0.016	0.000	0.886	0.020	0.000
Aluminum	β_{12}	-0.095	12.699	0.994	-0.206	0.022	0.000	-0.177	0.015	0.000
Tin	β_{13}	-0.104	13.913	0.994	0.224	0.032	0.000	0.032	0.017	0.059
Lead	β_{14}	-0.071	9.404	0.993	0.659	0.021	0.000	-0.018	0.015	0.212
Zinc	β_{15}	-0.198	27.337	0.994	-2.768	0.096	0.000	0.568	0.048	0.000
Nickel	β_{16}	-0.066	8.744	0.994	0.246	0.017	0.000	0.033	0.011	0.002
		B.3- Others								
Asymmetry	γ_1	0.0767	0.036	0.032	0.077	0.036	0.032	0.029	0.012	0.012
Unconditional Correlation with										
Aluminum	ρ_{21}				0.706	0.006	0.000			
Tin	ρ_{31}				0.453	0.004	0.000			
Lead	ρ_{41}				0.630	0.005	0.000			
Zinc	ρ_{51}				0.707	0.005	0.000			
Nickel	ρ_{61}				0.564	0.007	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 4. MGARCH parameter estimates - Aluminum -

		Diagonal			**CCC**			**DCC**		
		Coeff	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**
		Panel A: Mean equation								
Copper(-1)	φ_{21}	-0.042	0.010	0.000	-0.023	0.010	0.017	-0.012	0.007	0.093
Aluminum(-1)	φ_{22}	0.004	0.012	0.740	-0.017	0.011	0.139	-0.005	0.008	0.512
Tin(-1)	φ_{23}	-0.007	0.010	0.495	-0.006	0.010	0.498	-0.008	0.007	0.243
Lead(-1)	φ_{24}	-0.010	0.010	0.312	-0.012	0.009	0.125	-0.015	0.006	0.015
Zinc(-1)	φ_{25}	-0.031	0.010	0.001	-0.023	0.009	0.007	-0.035	0.007	0.00
Nickel(-1)	φ_{26}	0.009	0.007	0.184	0.009	0.007	0.187	0.009	0.005	0.071
		Panel B: Variance equation								
Constant	θ_2	0.075	0.038	0.047	0.075	0.038	0.048	0.230	0.017	0.000

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		B.1- ARCH effects								
Copper	α_{21}	-0.007	0.013	0.596	-0.042	0.044	0.337	-0.008	0.011	0.435
Aluminum	α_{22}	0.029	0.015	0.062	0.177	0.034	0.000	0.041	0.012	0.000
Tin	α_{23}	0.004	0.014	0.787	0.022	0.041	0.591	-0.019	0.009	0.036
Lead	α_{24}	0.006	0.013	0.962	-0.017	0..034	0.619	0.009	0.010	0.342
Zinc	α_{26}	0.004	0.012	0.767	0.023	0.038	0.555	-0.003	0.010	0.750
Nickel	α_{27}	0.007	0.012	0.545	-0.000	0.030	0.995	0.016	0.007	0.024
		B.2- GARCH effects								
Copper	β_{21}	0.070	7.188	0.992	-0.641	0.023	0.000	-0.209	0.023	0.000
Aluminum	β_{22}	0.972	0.005	0.000	0.548	0.009	0.000	0.482	0.021	0.000
Tin	β_{23}	0.111	11.373	0.992	-0.316	0.040	0.000	0.165	0.015	0.000
Lead	β_{24}	0.074	7.598	0.992	0.011	0.027	0.691	-0.054	0.017	0.001
Zinc	β_{25}	0.068	6.992	0.992	0.988	0.028	0.000	0.399	0.024	0.000
Nickel	β_{26}	0.068	7.044	0.992	0.253	0.024	0.000	0.176	0.019	0.000
		B.3- Others								
Asymmetry	γ_2	-0.016	0.020	0.423	-0.107	0.046	0.020	-0.031	0.011	0.00
Unconditional Correlation with										
Aluminum	ρ_{21}				0.706	0.006	0.000			
Tin	ρ_{32}				0.420	0.004	0.000			
Lead	ρ_{42}				0.567	0.005	0.000			
Zinc	ρ_{52}				0.646	0.006	0.000			
Nickel	ρ_{62}				0.493	0.004	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 5. MGARCH parameter estimates - Tin -

		Diagonal			**CCC**			**DCC**		
		Coeff	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**
		Panel A: Mean equation								
Copper(-1)	φ_{31}	-0.008	0.011	0.487	-0.005	0.012	0.668	-0.004	0.010	0.673
Aluminum(-1)	φ_{32}	-0.024	0.013	0.066	-0.024	0.015	0.101	-0.012	0.012	0.292
Tin(-1)	φ_{33}	-0.002	0.011	0.851	-0.006	0.012	0.606	0.008	0.010	0.428
Lead(-1)	φ_{34}	-0.006	0.010	0.551	-0.012	0.010	0.234	-0.017	0.009	0.040
Zinc(-1)	φ_{35}	-0.018	0.010	0.084	-0.018	0.011	0.112	-0.015	0.009	0.104
Nickel(-1)	φ_{36}	0.035	0.008	0.000	0.037	0.009	0.000	0.036	0.007	0.000
		Panel B: Variance equation								
Constant		0.244	0.039	0.000	-0.157	0.033	0.000	0.009	0.006	0.114
		B.1- ARCH effects								
Copper	α_{31}	0.103	0.079	0.189	0.153	0.058	0.0099	0.020	0.018	0.252

Aluminum	α_{32}	-0.119	0.078	0.126	0.011	0.077	0.887	-0.040	0.017	0.021
Tin	α_{33}	0.248	0.051	0.000	0.214	0.031	0.000	0.072	0.010	0.000
Lead	α_{34}	0.042	0.057	0.461	-0.086	0.041	0.037	0.009	0.011	0.403
Zinc	α_{35}	0.009	0.077	0.907	-0.029	0.054	0.593	-0.013	0.015	0.375
Nickel	α_{36}	-0.007	0.043	0.878	-0.040	0.034	0.238	0.007	0.010	0.459
		B.2- GARCH effects								
Copper	β_{31}	-0.071	9.404	0.993	0.659	0.021	0.000	-0.018	0.015	0.996
Aluminum	β_{32}	0.074	7.598	0.992	0.011	0.027	0.691	-0.054	0.017	0.000
Tin	β_{33}	0.722	0.011	0.000	0.237	0.016	0.000	0.880	0.013	0.000
Lead	β_{34}	0.140	6.989	0.983	-0.472	0.060	0.000	0.031	0.020	0.119
Zinc	β_{35}	0.148	7.366	0.983	5.685	0.153	0.00	-0.000	0.021	0.989
Nickel	β_{36}	0.125	6.236	0.983	1.045	0.082	0.000	0.017	0.021	0.426
		B.3- Others								
Asymmetry	γ_3	0.0273	0.074	0.713	0.082	0.050	0.101	0.003	0.012	0.767
Unconditional Correlation with										
Aluminum	ρ_{31}				0.453	0.004	0.000			
Tin	ρ_{32}				0.420	0.004	0.000			
Lead	ρ_{43}				0.390	0.003	0.000			
Zinc	ρ_{53}				0.418	0.005	0.000			
Nickel	ρ_{63}				0.402	0.003	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 6. MGARCH parameter estimates - Lead -

		Diagonal			**CCC**			**DCC**		
		Coeff	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**
		Panel A: Mean equation								
Copper(-1)	φ_{41}	-0.030	0.014	0.032	-0.025	0.012	0.046	-0.012	0.012	0.309
Aluminum(-1)	φ_{42}	-0.091	0.017	0.000	-0.096	0.015	0.000	-0.082	0.014	0.000
Tin(-1)	φ_{43}	-0.019	0.013	0.149	-0.012	0.012	0.326	-0.017	0.010	0.106
Lead(-1)	φ_{44}	0.079	0.012	0.000	0.071	0.011	0.000	0.083	0.009	0.000
Zinc(-1)	φ_{45}	0.034	0.013	0.012	0.023	0.011	0.040	0.007	0.010	0.518
Nickel(-1)	φ_{46}	-0.019	0.010	0.058	-0.014	0.009	0.124	-0.011	0.008	0.160
		Panel B: Variance equation								
Constant		0.185	0.042	0.000	-0.297	0.0612	0.000	0.546	0.036	0.000
		B.1- ARCH effects								
Copper	α_{41}	0.004	0.070	0.473	-0.062	0.060	0.3306	0.014	0.032	0.663
Aluminum	α_{42}	-0.095	0.063	0.130	-0.127	0.072	0.078	0.001	0.035	0.983
Tin	α_{43}	0.034	0.047	0.461	-0.009	0.053	0.869	-0.024	0.022	0.288

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Lead	α_{44}	0.187	0.043	0.000	0.173	0.032	0.000	0.126	0.021	0.000
Zinc	α_{45}	0.028	0.056	0.614	-0.032	0.053	0.546	-0.062	0.027	0.023
Nickel	α_{46}	-0.030	0.048	0.536	0.008	0.056	0.852	0.009	0.018	0.607
		B.2- GARCH effects								
Copper	β_{41}	-0.272	12.804	0.983	0.797	0.054	0.000	-0.303	0.019	0.000
Aluminum	β_{42}	-0.387	18.276	0.983	0.488	0.055	0.000	-1.901	0.086	0.000
Tin	β_{43}	-0.379	17.848	0.983	-0.007	0.061	0.905	0.517	0.031	0.000
Lead	β_{44}	0.839	0.006	0.000	0.443	0.008	0.000	0.583	0.019	0.000
Zinc	β_{45}	-0.235	11.070	0.983	0.014	0.016	0.371	1.356	0.064	0.000
Nickel	β_{46}	-0.251	11.839	0.983	-0.057	0.046	0.216	0.118	0.014	0.000
		B.3- Others								
Asymmetry	γ_4	-0.025	0.051	0.621	0.041	0.049	0.412	-0.020	0.022	0.384
Unconditional Correlation with										
Aluminum	ρ_{41}				0.630	0.005	0.000			
Tin	ρ_{42}				0.567	0.005	0.000			
Lead	ρ_{43}				0.390	0.003	0.000			
Zinc	ρ_{54}				0.678	0.009	0.000			
Nickel	ρ_{64}				0.520	0.004	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 7. MGARCH parameter estimates - Zinc -

		Diagonal			**CCC**			**DCC**		
		Coeff	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**
		Panel A: Mean equation								
Copper(-1)	φ_{51}	-0.026	0.013	0.035	-0.007	0.011	0.543	0.002	0.008	0.850
Aluminum(-1)	φ_{52}	-0.048	0.015	0.001	-0.061	0.014	0.000	-0.029	0.010	0.005
Tin(-1)	φ_{53}	0.001	0.012	0.883	0.008	0.011	0.514	-0.005	0.008	0.539
Lead(-1)	φ_{54}	0.000	0.010	0.979	0.003	0.010	0.724	0.008	0.006	0.195
Zinc(-1)	φ_{55}	-0.009	0.011	0.455	-0.022	0.011	0.039	-0.028	0.008	0.000
Nickel(-1)	φ_{56}	-0.011	0.009	0.227	-0.005	0.008	0.535	-0.008	0.006	0.195
		Panel B: Variance equation								
Constant		0.014	0.011	0.222	0.193	0.021	0.000	-0.010	0.005	0.062
		B.1- ARCH effects								
Copper	α_{51}	-0.009	0.015	0.576	0.025	0.032	0.431	-0.007	0.008	0.437
Aluminum	α_{52}	-0.014	0.024	0.557	0.001	0.028	0.961	-0.001	0.009	0.903
Tin	α_{53}	0.000	0.016	0.973	-0.083	0.025	0.001	0.009	0.007	0.200
Lead	α_{54}	0.005	0.014	0.746	0.038	0.018	0.036	0.003	0.005	0.550
Zinc	α_{55}	0.034	0.020	0.087	0.043	0.021	0.041	0.036	0.010	0.000

Nickel	α_{56}	0.001	0.013	0.961	0.001	0.016	0.929	-0.014	0.005	0.005
		B.2- GARCH effects								
Copper	β_{51}	-0.102	7.896	0.989	0.794	0.023	0.000	0.012	0.016	0.442
Aluminum	β_{52}	-0.140	10.929	0.989	0.417	0.023	0.000	0.014	0.018	0.422
Tin	β_{53}	-0.156	12.223	0.989	0.479	0.030	0.000	-0.016	0.016	0.284
Lead	β_{54}	-0.092	7.193	0.989	0.192	0.012	0.000	-0.006	0.011	0.581
Zinc	β_{55}	0.975	0.006	0.000	0.142	0.014	0.000	0.938	0.0123	0.000
Nickel	β_{56}	-0.097	7.532	0.989	-0.284	0.001	0.000	0.055	0.013	0.000
		B.3- Others								
Asymmetry	γ_5	0.003	0.020	0.873	-0.027	0.020	0.176	-0.005	0.007	0.487
Unconditional Correlation with										
Aluminum	ρ_{51}				0.707	0.005	0.000			
Tin	ρ_{52}				0.646	0.006	0.000			
Lead	ρ_{53}				0.418	0.005	0.000			
Zinc	ρ_{54}				0.678	0.009	0.000			
Nickel	ρ_{65}				0.551	0.004	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 8. MGARCH parameter estimates - Nickel -

		Diagonal			**CCC**			**DCC**		
		Coeff	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**	**Coeff**	**Std. Error**	**P-value**
		Panel A: Mean equation								
Copper(-1)	φ_{61}	0.023	0.018	0.209	0.051	0.017	0.002	0.040	0.014	0.005
Aluminum(-1)	φ_{62}	-0.093	0.024	0.000	-0.111	0.019	0.000	-0.076	0.017	0.000
Tin(-1)	φ_{63}	0.005	0.017	0.747	0.021	0.016	0.218	0.015	0.013	0.256
Lead(-1)	φ_{64}	-0.047	0.014	0.000	-0.063	0.013	0.000	-0.049	0.011	0.000
Zinc(-1)	φ_{65}	0.012	0.017	0.467	-0.001	0.015	0.946	-0.016	0.013	0.235
Nickel(-1)	φ_{66}	-0.007	00.012	0.537	0.007	0.012	0.534	0.018	0.009	0.060
		Panel B: Variance equation								
Constant	θ_6	0.074	0.022	0.000	0.594	0.101	0.000	0.673	0.04	0.000
		B.1- ARCH effects								
Copper	α_{61}	0.037	0.023	0.115	0.056	0.083	0.502	0.095	0.032	0.003
Aluminum	α_{62}	-0.079	0.029	0.008	-0.064	0.098	0.512	-0.046	0.033	0.160
Tin	α_{63}	-0.017	0.016	0.267	-0.095	0.073	0.194	-0.047	0.020	0.019
Lead	α_{64}	-0.000	0.0162	0.982	-0.009	0.054	0.869	-0.039	0.020	0.055
Zinc	α_{65}	0.027	0.018	0.126	-0.026	0.071	0.712	-0.008	0.026	0.755
Nickel	α_{66}	0.028	0.010	0.008	0.134	0.027	0.002	0.064	0.014	0.000
		B.2- GARCH effects								

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Copper	β_{61}	-0.202	0.994		2.821	0.071	0.000	-0.070	0.058	0.224
Aluminum	β_{62}	-0.288	39.961	0.994	1.077	0.071	0.000	-1.140	0.086	0.00
Tin	β_{63}	-0.272	37.560	0.994	0.486	0.061	0.000	0.120	0.037	0.001
Lead	β_{64}	-0.195	27.923	0.994	0.102	0.040	0.011	0.092	0.030	0.002
Zinc	β_{65}	-0.198	27.337	0.994	-2.768	0.096	0.000	0.568	0.048	0.000
Nickel	β_{66}	0.969	0.002	0.000	0.532	0.009	0.000	0.871	0.014	0.000
		B.3- Others								
Asymmetry	γ_6	0.003	0.014	0.823	2.886	0.026	0.000	8.424	0.253	0.000
Unconditional Correlation with										
Aluminum	ρ_{61}				0.563	0.007	0.000			
Tin	ρ_{62}				0.493	0.004	0.000			
Lead	ρ_{63}				0.402	0.003	0.000			
Zinc	ρ_{64}				0.520	0.004	0.000			
Nickel	ρ_{65}				0.551	0.004	0.000			
Log Likelihood		-45375.37			-40853.87			-40228.84		
AIC		22.317			20.241			19.800		
SBC		22.505			20.452			19.990		

Table 9. Diagnostic tests for standardized residuals

		$LB(20)$	$p-value$	$LB^2(20)$	$p-value$
Diagonal	Copper	29.140	0.085	15.570	0.743
	Aluminum	12.952	0.879	25.482	0.184
	Tin	25.878	0.170	17.977	0.589
	Lead	27.581	0.120	25.005	0.201
	Zinc	14.736	0.791	22.675	0.305
	Nickel	36.716	0.012	46.666	6.52e-004
CC	Copper	25.885	0.170	207.149	4.31e-033
	Aluminum	13.398	0.860	75.233	2.49e-008
	Tin	23.398	0.270	19.540	0.487
	Lead	34.031	0.026	59.264	9.25 e-006
	Zinc	15.176	0.766	65.070	1.14 e-006
	Nickel	38.924	0.007	199.654	1.32 e-031
DCC	Copper	21.414	0.373	47.343	5.25 e-004
	Aluminum	11.415	0.935	74.082	3.87 e-008
	Tin	20.549	0.424	20.159	0.448
	Lead	29.257	0.083	50.596	1.82 e-004
	Zinc	13.101	0.873	45.788	8.62 e-004
	Nickel	30.732	0.059	43.039	0.002

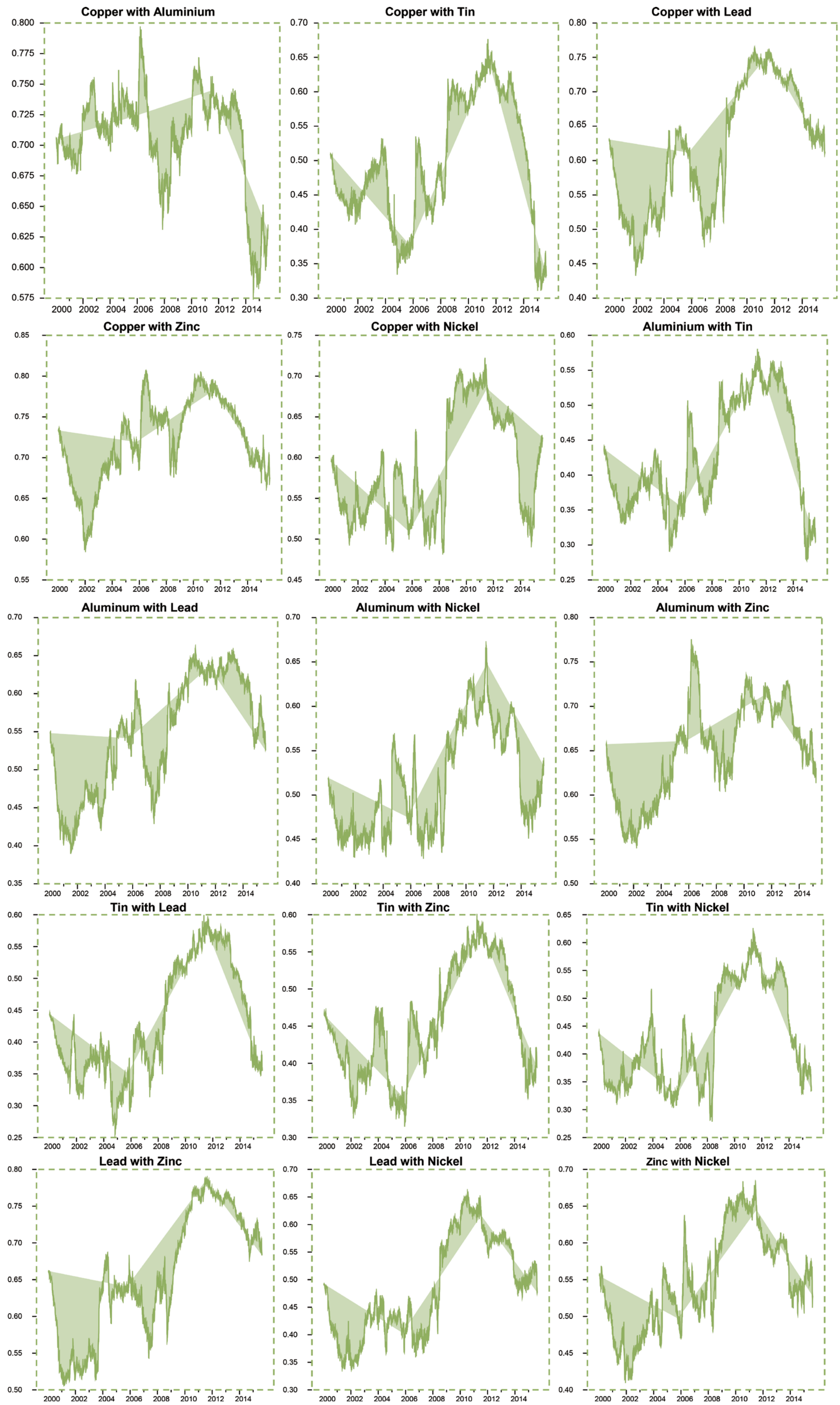

Figure 5. Conditional Correlations

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Table 9. Hedge ratio (long/short) - summary statistics -

Series	Observation	Mean	Std Error	Minimum	Maximum
		HEDGES(1,1)	0		
HEDGES(2,1)	4076	0.630566	0.115727	0.264615	0.967199
HEDGES(3,1)	4076	0.507234	0.173376	0.215623	1.191813
HEDGES(4,1)	4076	0.768566	0.174380	0.333055	1.838848
HEDGES(5,1)	4076	0.814677	0.159220	0.409076	1.335781
HEDGES(6,1)	4076	0.865242	0.148360	0.507566	2.132039
HEDGES(1,2)	4076	0.819414	0.168956	0.505849	1.893161
		HEDGES(2,2)	0		
HEDGES(3,2)	4076	0.498855	0.183644	0.193556	1.508843
HEDGES(4,2)	4076	0.770248	0.176571	0.353550	1.848327
HEDGES(5,2)	4076	0.838703	0.171274	0.401294	1.378859
HEDGES(6,2)	4076	0.862331	0.133327	0.500126	1.866763
HEDGES(1,3)	4076	0.523248	0.137742	0.180561	1.000348
HEDGES(2,3)	4076	0.396628	0.115784	0.140882	0.790594
		HEDGES(3,3)	0		
HEDGES(4,3)	4076	0.551568	0.151396	0.139391	1.621557
HEDGES(5,3)	4076	0.535774	0.163569	0.157625	1.218470
HEDGES(6,3)	4076	0.662150	0.193625	0.192879	1.972066
HEDGES(1,4)	4076	0.515784	0.121522	0.137081	1.015252
HEDGES(2,4)	4076	0.402483	0.112965	0.128196	0.744349
HEDGES(3,4)	4076	0.360531	0.133324	0.075685	0.933866
		HEDGES(4,4)	0		
HEDGES(5,4)	4076	0.605880	0.135031	0.192560	1.162611
HEDGES(6,4)	4076	0.582650	0.124375	0.157975	1.259634
HEDGES(1,5)	4076	0.656984	0.104306	0.357751	1.164959
HEDGES(2,5)	4076	0.521217	0.091080	0.313512	0.865244
HEDGES(3,5)	4076	0.419854	0.153007	0.164343	1.082035
HEDGES(4,5)	4076	0.730093	0.141572	0.350861	1.615435
		HEDGES(5,5)	0		
HEDGES(6,5)	4076	0.730801	0.145162	0.353114	2.223810
HEDGES(1,6)	4076	0.413421	0.111868	0.146432	0.815846
HEDGES(2,6)	4076	0.320094	0.095422	0.126423	0.647588
HEDGES(3,6)	4076	0.315438	0.152992	0.068006	0.927964
HEDGES(4,6)	4076	0.425182	0.158420	0.108793	1.225799
HEDGES(5,6)	4076	0.437466	0.146951	0.104247	0.905048

Note: 1= Copper, 2= Aluminum, 3= Tin, 4= Lead, 5= Zinc, 6=Nickel.

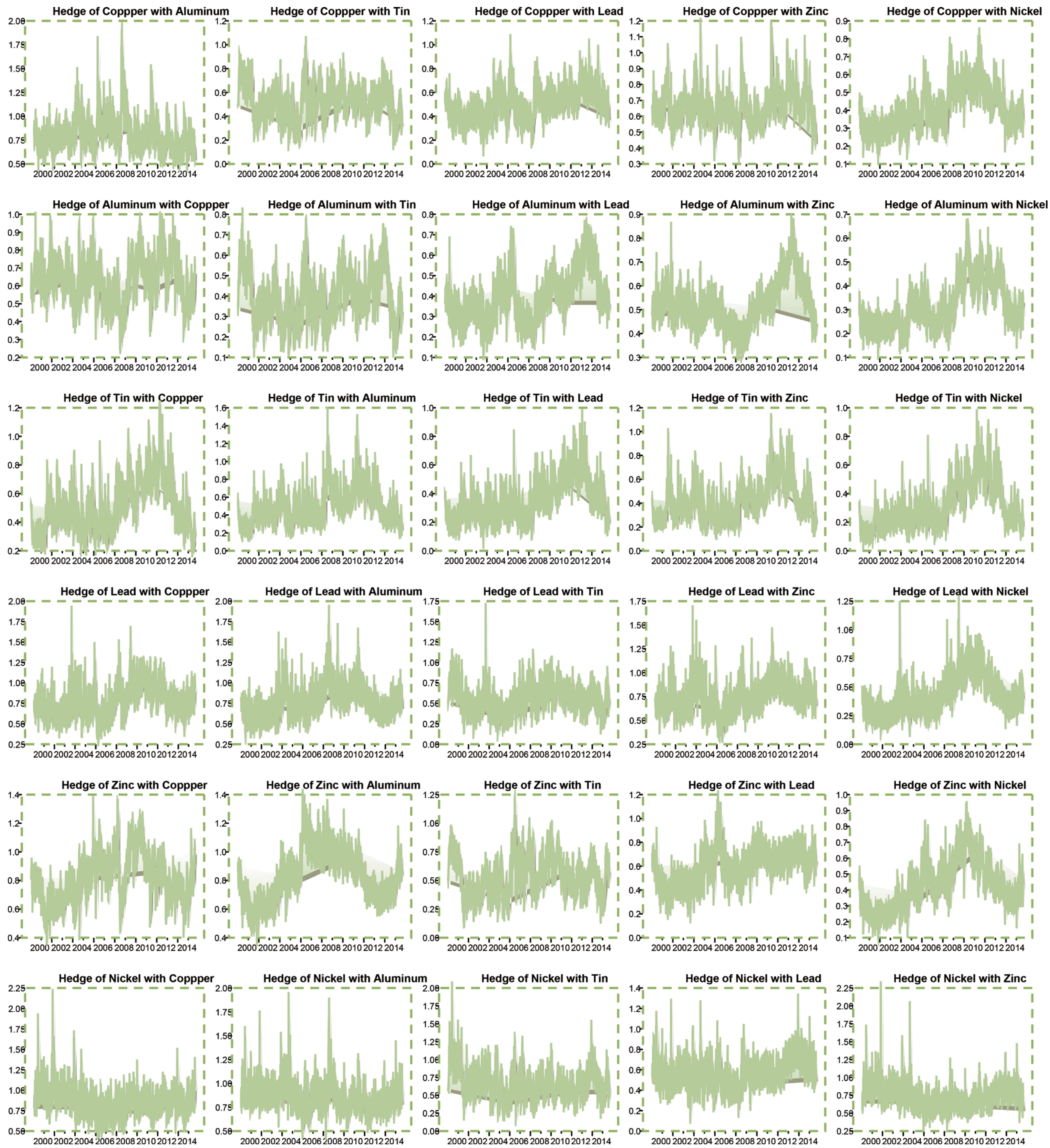

Figure 6. Time-varying hedge ratios computed from DCC model

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Table 10. portfolio weights -summary statistics-.

	Mean	Std. dev	Minimum	Maximum
Aluminum/Copper	0.34	0.25	0.00	0.96
Tin/Copper	0.49	0.23	0.00	1.00
Tin/Aluminum	0.58	0.21	0.07	1.00
Lead/Copper	0.73	0.21	0.00	1.00
Lead/Aluminum	0.79	0.17	0.23	1.00
Lead/Tin	0.67	0.18	0.04	1.00
Zinc/Copper	0.67	0.25	0.00	1.00
Zinc/Aluminum	0.77	0.20	0.10	1.00
Zinc/Tin	0.59	0.23	0.00	1.00
Zinc/Lead	0.37	0.22	0.00	1.00
Nickel/Copper	0.87	0.13	0.31	1.00
Nickel/Aluminum	0.90	0.10	0.43	1.00
Nickel/Tin	0.76	0.20	0.03	1.00
Nickel/Lead	0.64	0.20	0.00	1.00
Nickel/Zinc	0.74	0.20	0.09	1.00

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