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Contagion in Futures Metal Markets during the Recent Global Financial Crisis: Evidence from Gold, Silver, Copper, Zinc and Aluminium

Konstantinos Tsiaras

Department of Economic Sciences. University of Ioannina, Greece.
Email: konstantinos.tsiaras1988@gmail.com

Abstract

This paper seeks to investigate the time-varying dynamic conditional correlations to the five most important future metal markets, namely Gold, Silver, Copper, Zinc and Aluminium. We employ a multivariate Fractionally Integrated Generalized ARCH (FIGARCH) dynamic conditional correlation (cDCC) model to generate the potential contagion effects between the markets. The under investigation period is during the period 2006-2011. Empirical results show the existence of contagion or the increase in dynamic conditional correlation for all the pairs of markets, indicating the correlations risky from an investor's point of view and implying the portfolio strategies difficult to apply. Additionally, Zinc is proved to be the most immune future metal market. The results are of interest to policymakers who provide regulations for the future metal markets.

JEL Codes: C58, C61, G11, G15, L61.
Keywords: Financial contagion, Global Financial Crisis, cDCC-FIGARCH model, future metal market

1. Introduction

Volatility modeling is now at the center of financial investigation literature (Billio and Caporin, 2010; Dimitriou and Kenourgios, 2015; Li and Giles, 2015). The measurement of volatility using MGARCH models is very important in order to predict the consequences of the risk transfer from one financial market to another financial market (Mensi, Beljid, Boubaker and Managi, 2013; Thuraisamy, Sharma and Ahmed, 2013; Aboura and Chevallier, 2015). Based on volatility prediction, investors can hold a portfolio consisting of financial assets from financial markets presenting no serious risk transfer (Vivian and Wohar, 2012; Sensoy, 2013).

Gold, silver and copper are the most important metals traded on COMEX (Commodity Exchange, Inc) and zinc and aluminium are the most important metals traded on NYMEX (New York Mercantile Exchange). The benefits of important futures metal markets are many, i.e. portfolio diversification, managing contract expiration, the power of leverage, among others (Baur and McDermott, 2010; Baur and Lucey, 2010; Alonso, Field and Kirchain, 2012). Risk transfer between futures metal markets is of great importance for investors and policy makers.

There is not an extensive literature analyzing potential volatility spillovers between futures metal markets (Chen, 2010; Mutafoglu, Tokat and Tokat, 2012). However, the link between those markets is of great importance. Even the link between metals themselves has not still attracted great attention. Previous empirical studies have examined the static spillover effects (Tao and Green, 2012; Wu, Li and Zhang, 2005; Booth, Chowdhury, Martikainen and Tse, 1996; Hamao, Masulis and Ng, 1990). Still, there are not a great number of papers, investigating the dynamic spillover effects between future markets returns. We present some research of futures markets dynamic spillovers as follows.

Antonakakis, Kizys and Floros (2014) examine the dynamic spillover effects between spot and futures market volatility, volume of futures trading and open interest in the UK and the USA. They use daily data for a period from 25/02/2008 until 14/03/2013, entailing both the global financial crisis and the Eurozone debt crisis. They find that spot and futures volatilities in the UK are net receivers of shocks to volume of futures trading and open interest. In addition, they prove that the spot and futures volatility spillovers between the UK and USA markets are of bidirectional nature, while, they are affected by major economic events such as the global financial and Eurozone debt crisis.

Sensoy, Hachahsanoglu and Nguyen (2015) examine the dynamic comovement of commodity futures returns within each category (energy, precious metals, industrial metals, and agriculture) for the period 1997-2013. The data frequency is daily and they use a cDCC-GARCH model. They find evidence of convergence for precious and industrial metal commodity futures since mid2000s. Moreover, there is no sign of convergence across the agricultural commodity futures, with most of them moving in an unrelated manner. Finally, they find a relatively high level of convergence for energy commodity futures, except for natural gas futures which expectedly behave significantly different from the other energy commodity futures.

Behmiri, Manera and Nicolini (2016) estimate a multivariate GARCH model to obtain the dynamic conditional correlations between 10 commodities in energy, metals and agriculture futures markets over the period 1998- 2014. The dynamic conditional correlations increased sharply around year 2008 and subsequently decreased. To understand this trend, they look at the factors influencing those correlations. Adopting a pooled mean group (PMG) estimator, they notice that macroeconomic variables are significantly correlated with the agriculture-energy and metals-energy dynamic conditional correlations. Financial factors as well as speculative activity are statistically significant in explaining the agriculture-energy correlations but not the dynamic conditional correlations between metals and energy.

Kang, Mclver and Yoon (2017) investigate the spillover effects among six commodity futures markets, namely gold, silver, West Texas Intermediate crude oil, corn, wheat, and rice during 2002-2016. They used weekly closing prices and they employ the multivariate DECO-GARCH model and the spillover index, during the recent global financial and European sovereign debt crises. They find evidence of increased equicorrelation during crises. Regarding volatility spillovers, they find more pronounced trends in the post-crisis period. They prove that gold and silver are information transmitters, while the rest futures were receivers of spillovers during periods of financial stress.

The present research answers several questions, considering the futures metal markets. (ⅰ) what are the distributional properties of the five futures market returns? (ⅱ) is the dynamic conditional correlation between the futures markets positive and volatile during the recent Global Financial Crisis (GFC) (2007)? (iii) are there evidence of contagion effects?

The remainder of this paper is organized as follows. Second section presents the FIGARCH-cDCC model and the log-likelihood estimation. Third section provides the data. The empirical results and their economic explanation are displayed and discussed in the fourth section. Last section concludes the study.

2. The Model

We use the univariate FIGARCH(p,d,q) model to quantify the standardized residuals (first subsection). Then, we use the estimated standardized residuals to produce the multivariate conditional variance matrix by employing a cDCC model (second subsection). In the last subsection, we present the log-likelihood function.

2.1 Univariate FIGARCH(p,d,q) model

By using a constant (μ), the empirical set-up of the mean equation for the daily future market returns (y_t) is represented by the following equation:

$$y_t = \mu + \varepsilon_t, \text{ with } t = 1,\ldots,T. \tag{1}$$

ε_t is the standardized residuals such that:

$$\varepsilon_t = \sqrt{h_t}u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \sim N(0,1) \tag{2}$$

where h_t is defined as the univariate conditional variance matrix and u_t is the standardized errors. Furthermore, H_t is the multivariate conditional variance matrix.

It follows the definition of the univariate FIGARCH(*p,d,q*) model (Baillie, Bollerslev and Mikkelsen; 1996) to generate the conditional variance matrix (h_t):

$$h_t = \omega[1 - b(L)]^{-1} + \{1 - [1 - b(L)]^{-1}\Phi(L)(1 - L)^d\}\varepsilon_t^2 \tag{3}$$

where ω is mean of the logarithmic conditional variance, $\Phi(L) = [1 - a(L) - b(L)](1 - L)^{-1}$ is lag polynomial of order p and $(1 - L)^d$ is fractional difference operator. Additionally, $b(L)$ and $a(L)$ are autoregressive polynomials of order p and q so that: $b(L) = 1 - \sum_{k=1}^{P} b_k L^k$ and $a(L) = 1 + \sum_{l=1}^{q} a_l L^l$.

Furthermore, the selected lag order is equal to 1, as many other researchers have mentioned as sufficient to estimate the univariate conditional variance matrix, i.e. Bolleslev, Chou and Kroner (1992), among others.

2.2 Multivariate cDCC model

We define the multivariate conditional variance matrix (H_t) (*N x N* matrix), using the cDCC model of Aielli (2009) as follows:

$$H_t = D_t R_t D_t \tag{4}$$

and

$$D_t = diag\left(h_{11t}^{\frac{1}{2}} \ldots h_{NNt}^{\frac{1}{2}}\right), \text{ where } N \text{ is the number of markets } (i = 1,\ldots,N) \tag{5}$$

Additionally, we define the conditional correlation matrix (R_t):

$$R_t = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \tag{6}$$

We define $P_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}\right)$ and $u_t^* = P_t u_t$.

The cDCC model of Aielli (2009) is an extension of the DCC model of Engle (2002). In the cDCC model, $Q_t = (q_{ij,t})$ (*N x N* symmetric positive definite matrix) is defined as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}^* u_{t-1}^{*\prime} + \beta Q_{t-1} \tag{7}$$

where $\bar{Q}$ is the *N x N* unconditional variance matrix of u_t^* (since $\mathrm{E}[u_t^* u_t^{*\prime} | \Omega_{t-1}] = Q_t$)[1]. α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

For the cDCC model, the estimation of the matrix $\bar{Q}$ and the parameters α and β are intertwined, since $\bar{Q}$ is estimated sequentially by the correlation matrix of the u_t^*. To obtain u_t^* I need however a first step estimator of the diagonal elements of Q_t. Thanks to the fact that the diagonal elements of Q_t do not depend on $\bar{Q}$ (because $\overline{Q_{ii}} = 1$ for $i = 1,\dots,N$), Aielli (2009) proposed to obtain these values $q_{11,t}, \dots, q_{NN,t}$ as follows:

$$q_{ii,t} = (1 - \alpha - \beta) + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1} \tag{8}$$

for $i = 1,\dots,N$. In short, given α and β, we can compute $q_{11,t}, \dots, q_{NN,t}$ and thus u_t^*, then we can estimate $\bar{Q}$ as the empirical covariance of u_t^*.

2.3 Log-likelihood estimation

We estimate the model using Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors as follows:

$$\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{\nu+k}{2}\right)}{[\nu\pi]^{\frac{k}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{k}{2}}} - \frac{1}{2}\log(|H_t|) - \left(\frac{k+\nu}{2}\right)log\left[1+\frac{\varepsilon_t{}' H_t{}^{-1}\varepsilon_t}{\nu-2}\right]\right] \tag{9}$$

where $\Gamma(.)$ is the Gamma function, k is the number of equations, and ν is the degrees of freedom.

3. Data Characteristics

We use daily data for five future metal markets, namely Gold, Silver, Copper, Zinc and Aluminium. All data is obtained from *Datastream® Database*. While Gold, Silver and Copper are traded on COMEX (Commodity Exchange, Inc), Zinc and Aluminium are traded on NYMEX (New York Mercantile Exchange) and prices in USD. The sample period entail the crisis period: from 28th December 2006 until 5th October 2011. We define the end of the period one day after the S&P 500 faced a decline of 21.58% for last time after GFC. We use 1245 observations for each market. Future market returns are generated by $r_t = log(p_t) - log(p_{t-1})$, where p_t is the price of future market on day *t*.

In Table 1 above, we see the summary statistics for future metal market returns. All future metal market returns are negatively skewed. Additionally, Silver exhibits larger fluctuations compared to the rest markets, considering the highest maximum and the lowest minimum return prices. Moreover, all market returns present excess kurtosis (fat tails). According to the

[1] Aielli (2009) has recently shown that the estimation of $\bar{Q}$ as the empirical correlation matrix of u_t is inconsistent because: $\mathrm{E}[u_t\ u_t\ ] = \mathrm{E}[\mathrm{E}[u_t' u_t\ |\Omega_{t-1}] = \mathrm{E}[R_t\ ] \neq \mathrm{E}[Q_t\ ]$.

Jarque-Bera statistic, we reject the null hypothesis of normality for all markets, suggesting the use of student-*t* distribution as the most appropriate for the empirical analysis (Forbes and Rigobon, 2002). All of the series were subjected to unit-root testing using SCHMIDT-PHILLIPS test, suggesting daily returns appropriate for further testing. Applied to the full sample, the Hurst-Mandelbrot R/S test and the Lo R/S test statistics (q=2) show the existence of long-range dependence at the 99%

Table 1. Summary statistics of daily future market returns, sample period: 28th December, 2006 – 4th October, 2011.

	Gold	Silver	Copper	Zinc	Aluminium
Panel A: descriptive statistics					
Mean	0,00033191	0,00030056	2,4472e-005	-0,00029884	-8,7434e-005
Minimum	-0,026294	-0,084768	-0,050245	-0,049059	-0,032699
Maximum	0,037458	0,053672	0,050996	0,041218	0,025994
Std. Deviation	0,0058656	0,010731	0,009911	0,011276	0,0072251
Panel B: Normality Test					
Skewness	-0,043510	-0,89367***	-0,18803***	-0,082953	-0,23437***
t-Statistic	0,62725	12,883	2,7108	1,1959	3,3788
p-Value	0,53049	5,5772e-038	0,0067127	0,23174	0,00072799
Excess Kyrtosis	3,8900***	6,2342***	2,3765***	0,86188***	1,1789***
t-Statistic	28,062	44,973	17,144	6,2176	8,5043
p-Value	2,8235e-173	0,00000	6,9532e-066	5,0494e-010	1,8269e-017
Jarque-Bera	784,74	2180,1	300,08	39,930	83,423
p-Value	3,9423e-171	0,00000	6,9039e-066	2,1343e-009	7,6724e-019
Panel C: Unit Root Test					
SCHMIDT-PHILLIPS Test (rho)	-1085,51	-1137,94	-1361,7	-1261,58	-1107,02
Critical value: 1%	-25,2	-25,2	-25,2	-25,2	-25,2
Critical value: 5%	-18,1	-18,1	-18,1	-18,1	-18,1
Critical value: 10%	-15	-15	-15	-15	-15
Panel D: Autocorrelation and long-term dependence tests					
Hurst-Mandelbrot R/S test statistics	1,01835	1,45083	1,57735	1,46189	1,5791
Lo R/S test statistics (q=2)	1,00543	1,41254	1,65551	1,49277	1,58117
Critical value: 90%	[0,861, 1,747]	[0,861, 1,747]	[0,861, 1,747]	[0,861, 1,747]	[0,861, 1,747]
Critical value: 95%	[0,809, 1,862]	[0,809, 1,862]	[0,809, 1,862]	[0,809, 1,862]	[0,809, 1,862]
Critical value: 99%	[0,721, 2,098]	[0,721, 2,098]	[0,721, 2,098]	[0,721, 2,098]	[0,721, 2,098]

Notes: SCHMIDT-PHILLIPS Test is with 2 lags. *** denote statistical significance at the 1% level.

Appendix A shows the actual series of future markets and their respective logarithmic returns for Gold (Graph A), Silver (Graph B), Copper (Graph C), Zinc (Graph D) and Aluminium (Graph E). All series exhibit a great deal of volatility, indicating heteroskedasticity. The above conclusion rationalizes the use of the dynamic conditional correlations (cDCC) in the multivariate FIGARCH(1,d,1) framework.

4. Empirical results

We divide this section into three subsections. First subsection presents the empirical results from the cDCC-AR(1)-FIGARCH(1,d,1) model. Second subsection states the mean values of conditional variance and covariance characteristics. In the third subsection, we show the dynamic conditional correlation coefficients characteristics.

Table 2. Estimates of FIGARCH(1,d,1) model, sample period: 28th December, 2006 – 4th October, 2011.

	Gold	Silver	Copper	Zinc	Aluminium
constant *(μ)*	0,000574***	0,001021***	0,000596***	0,000015	0,000035
t-Statistic	4,698	4,760	2,784	0,05083	0,1882
p-Value	0,0000	0,0000	0,0054	0,9595	0,8508
constant *(ω)*	0,347676	0,034654	3,188002**	0,078095	1,854400
t-Statistic	1,363	1,892	2,026	1,575	0,9889
p-Value	0,1732	0,0587	0,0430	0,1154	0,3229
d-Figarch	0,933231***	0,511239***	0,567434***	0,365602***	0,491073
t-Statistic	6,331	3,079	3,708	3,515	1,702
p-Value	0,0000	0,0021	0,0002	0,0005	0,0889
ARCH *(α)*	0,024720	0,355381***	0,160819**	0,359273***	0,241829**
t-Statistic	0,2192	4,012	2,222	3,656	2,344
p-Value	0,8265	0,0001	0,0264	0,0003	0,0192
GARCH *(b)*	0,922545***	0,732037***	0,686380***	0,659487***	0,726047***
t-Statistic	18,44	6,083	5,641	5,151	3,737
p-Value	0,0000	0,0000	0,0000	0,0000	0,0002

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively.

4.1 Empirical results of the cDCC- FIGARCH(1,d,1) model

Table 2 above states that all markets exhibit significant constant (*μ)* in the mean equation (Equation 1) except the case of Zinc. FIGARCH results (Equation 3) show significant constant (*ω*) only for Copper. Additionally, all markets demonstrate strong persistent behaviour (significant *d*-Figarch). Interestingly, we notice significant ARCH effects (*α*) for all markets except the case of Gold. All markets show significant GARCH effects (*b*).

Table 3. Estimates of cDCC model, degrees of freedom, log-likelihood, diagnostic tests and information criteria, sample period: 28th December, 2006 – 4th October, 2011.

	Gold-Silver	Gold-Copper	Gold-Zinc	Gold-Aluminium
Panel A: estimates of cDCC model				
Average CORij	0,846912***	0,450417***	0,341664***	0,035823
t-Statistic	43,79	7,549	8,298	1,063
p-Value	0,0000	0,0000	0,0000	0,2882
alpha *(α)*	0,045610***	0,081033***	0,098038***	0,005119
t-Statistic	3,256	4,083	2,878	0,7827
p-Value	0,0012	0,0000	0,0041	0,4339
beta *(β)*	0,926641***	0,887566***	0,773116***	0,969532***
t-Statistic	26,29	29,82	8,866	77,29
p-Value	0,0000	0,0000	0,0000	0,0000
degrees of freedom *(v)*	4,744558***	6,081301***	7,206750***	7,237091***
t-Statistic	10,57	8,359	7,201	7,020
p-Value	0,0000	0,0000	0,0000	0,0000
log-likelihood	9595,260	9052,609	8717,139	9203,949
Panel B: diagnostic tests				
$x^2(4)$	298,47**	243,51**	176,00**	215,27**
p-Value	0,0000	0,0000	0,0000	0,0000
Hosking (50)	194,461	221,881	209,758	346,527
p-Value	0,5972059	0,1379564	0,3038372	0,0000000
Hosking^2 (50)	203,620	177,847	166,776	176,420

p-Value	0,3770548	0,8450659	0,9480340	0,8627405
Li-McLeod (50)	194,938	221,656	209,535	345,955
p-Value	0,5877815	0,1402800	0,3076263	0,0000000
Li-McLeod^2 (50)	204,242	178,094	167,555	176,975
p-Value	0,3654797	0,8418682	0,9432039	0,8560221
Panel C: Information Criteria				
Akaike	0,010107	0,010809	0,011242	0,010613
Schwarz	0,067796	0,068498	0,068931	0,068302

Notes: The symmetric positive definite matrix Q_t is generated using one lag of Q and of u^*. P-values have been corrected by 2 degrees of freedom for Hosking2 (50) and Li-McLeod2 (50) statistics. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

In Table 3 above, we report the results of cDCC model estimations (Equation 7 and Equation 9). We observe the strongest average correlation (CORij) between Gold and Silver. Moreover, we see significant ARCH effects (α) except the case of Gold-Aluminium, while all pairs of markets exhibit significant GARCH effects (β). In addition, we present the degrees of freedom and the log-likelihood. Based on $x^2(8)$ statistic results, we reject the null hypothesis of no spillovers at 1% significance level. Ljuing-Box test results (Hosking, 1980; Li-McLeod, 1983) state evidence of no serial autocorrelation, indicating the absence of misspecification errors. Additionally, we provide the AIC and SIC information criteria for our model.

4.2 Mean values of conditional variance and covariance charasteristics

In table 4 below, we present the estimated mean values ($\overline{h_{ij}}$, with $i, j = 1, \dots, N$) of conditional variances and covariances. First, we generate and store the conditional variances and covariances using the FIGARCH-cDCC model. In addition, we estimate the mean values for the conditional variances and covariances. We make the assumption that the mean values are reflecting the own volatility and the cross-volatility spillovers.

Table 4. Mean values of conditional variance and covariance ($\overline{h_{i,j}}$), sample period: 28th December, 2006 – 4th October, 2011.

Market i	Gold (i=1)	Silver (i=2)	Copper (i=3)	Zinc (i=4)	Aluminium (i=5)
($\overline{h_{i,1}}$)	3,6175e-005	-	-	-	-
($\overline{h_{i,2}}$)	5,4235e-005	0,00011972	-	-	-
($\overline{h_{i,3}}$)	2,3607e-005	-	0,00010594	-	-
($\overline{h_{i,4}}$)	2,1392e-005	-	-	0,00013717	-
($\overline{h_{i,5}}$)	1,5788e-006	-	-	-	5,6085e-005

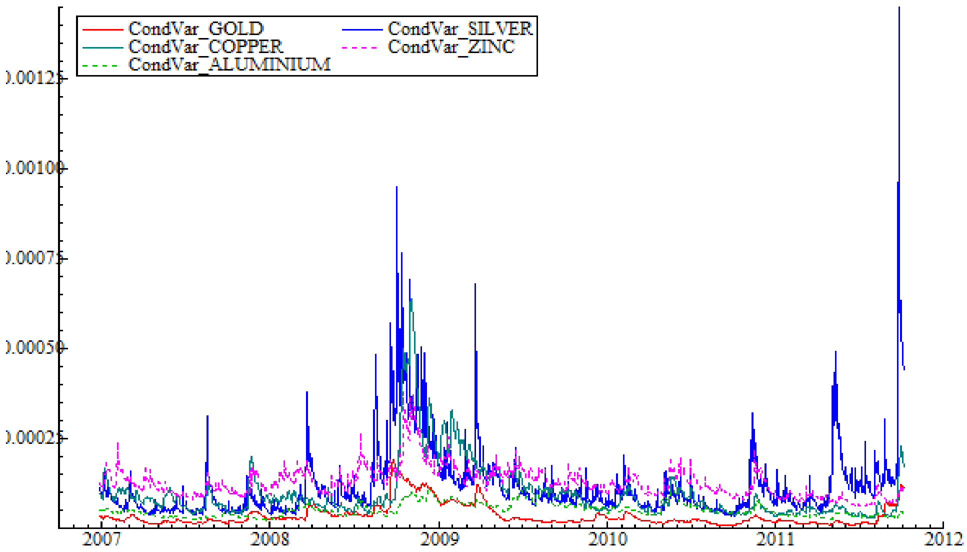
Regarding the own volatility effects, we observe that $\overline{h_{4,4}} > \overline{h_{2,2}} > \overline{h_{3,3}} > \overline{h_{5,5}} > \overline{h_{1,1}}$, revealing Zinc future market's strong own effects. The highest own volatility of Zinc future market is interpretable given the fact that participants in this market prefer to book profits coupled with muted demand from consuming industries in the physical market mainly weighed on zinc prices at futures trade.

For the cross-volatility spillovers, we note that $\overline{h_{1,2}} > \overline{h_{1,3}} > \overline{h_{1,4}} > \overline{h_{1,5}}$. The above results suggest that spillover effects for the pairs of countries Gold-Silver ($\overline{h_{1,2}}$) and Gold-Copper ($\overline{h_{1,3}}$) are relatively stronger. Additionally, all the cross-volatility spillover effects are approximately the same, suggesting a level of integration and interdependence.

Figure 1 below graphs the estimated conditional variances for Gold, Silver, Copper, Zinc and Aluminium. We observe that all markets have extremely volatility levels. Interestingly, all variances exhibit the largest fluctuations at the end of 2008. In addition, aluminium demonstrates the most volatile conditional variance among all the markets.

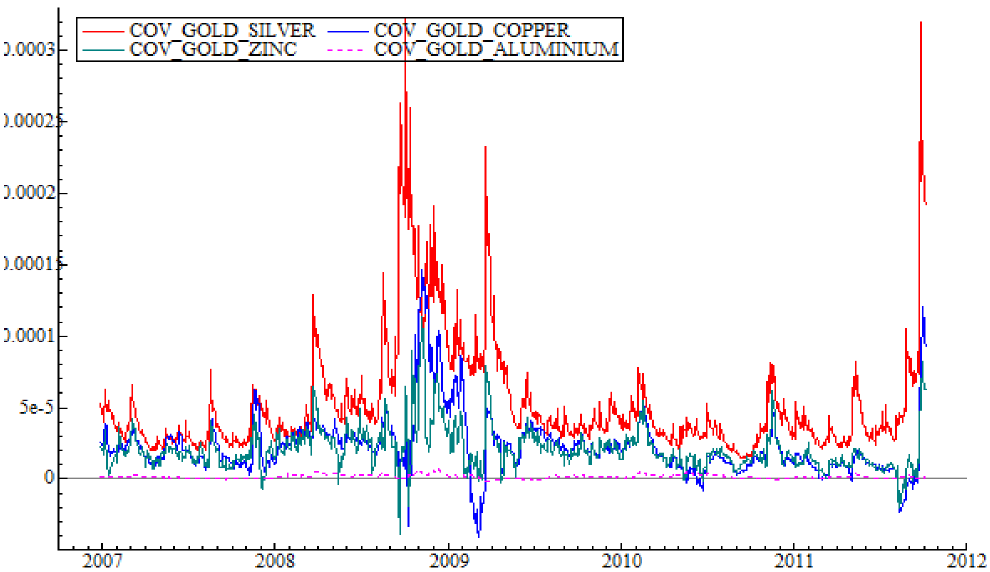
Figure 2 below presents the conditional covariances. Results state only positive values for the conditional covariance between Gold and Silver . In addition, we observe mostly positive values for the conditional covariances for the market pairs Gold-Copper, Gold-Zinc and Gold-Aluminium.

Figure 1. Conditional variances of the univariate FIGARCH(1,d,1) model



Notes: The red lines represent the conditional variance (h_t) for all futures markets, generated by Equation 3.

Figure 2. Conditional covariances of the bivariate FIGARCH(1,d,1)-cDCC model



Notes: The red lines represent the conditional covariances of the bivariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 4.

4.3 Dynamic conditional correlation coefficients characteristics

In table 5 below, we report the descriptive statistics of the dynamic conditional correlations (DCCs) of the four pairs of markets. The highest mean value (0,83398) is between gold and silver. In addition, the DCC between gold and copper experiences larger flunctuations considering the lowest minimum value (-0,45194), the second highest maximum value (0,7869) and the highest std. deviation value (0,20433). The Skewness, Excess Kyrtosis and the Jarque-Bera test statistics indicate that the DCCs for the pairs of markets gold-silver, gold-copper and gold-zinc are not normally distributed. We analyze the pair-wise DCCs as follows.

Table 5. Statistical properties of the Multivariate FIGARCH-cDCC's, sample period: 28th December, 2006 – 4th October, 2011.

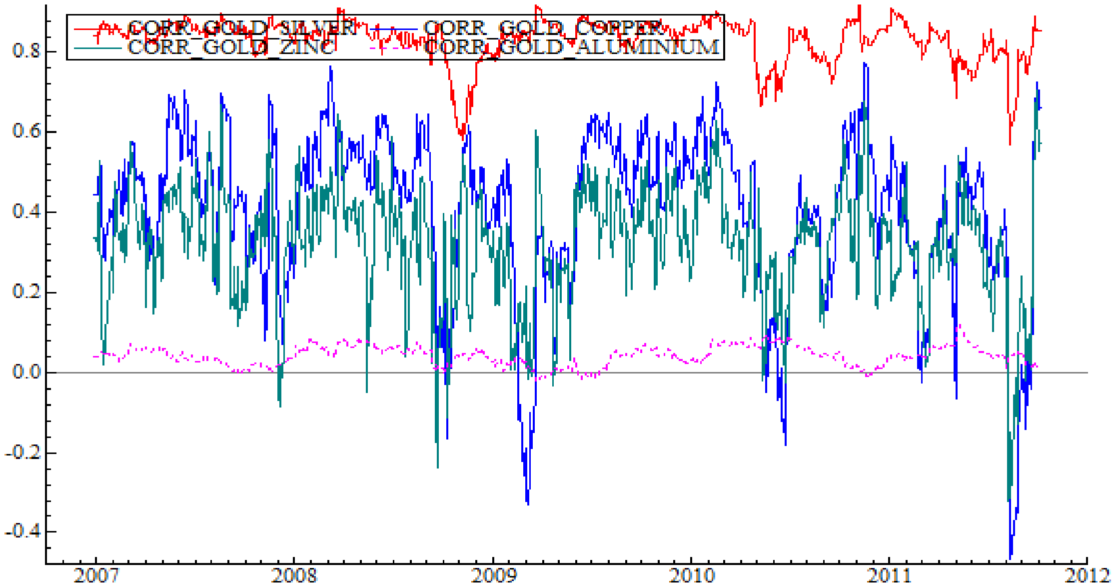
	Gold-Silver	Gold-Copper	Gold-Zinc	Gold-Aluminium
Panel A: descriptive statistics				
Mean	0,83398	0,40991	0,32498	0,039142
Minimum	0,57723	-0,45194	-0,34819	-0,021179
Maximum	0,91981	0,7869	0,72306	0,11453
Std. Deviation	0,051676	0,20433	0,`4916	0,022312
Panel B: Normality Test				
Skewness	-1,8618***	-1,2644***	-0,68728***	-0,048403
t-Statistic	26,840	18,228	9,9081	0,69780
p-Value	1,0984e-158	3,0882e-074	3,8388e-023	0,48530
Excess Kyrtosis	4,3546***	1,8539***	1,2804***	-0,20266
t-Statistic	31,414	13,374	9,2365	1,4620
p-Value	1,3157e-216	8,6019e-041	2,5459e-020	0,14375
Jarque-Bera	1701,5	509,61	182,91	2,6145
p-Value	0,00000	2,1869e-111	1,9153e-040	0,27056

Notes: *** denote statistical significance at the 1% level.

As shown in figure 3 below, the DCC coefficient between Gold and Silver has positive values and it is persistently high, indicating a risky correlation from an investor's perspective. Additionally, it presents two major troughs (4th November 2008 and 5th August 2011) due to the following reasons: (1) in 4th November 2008, the USA presidential election was held, and (2) in 5th August 2011, Standard & Poor's credit rating agency downgraded the credit rating of the USA from AAA to AA+.

Next, in figure 3 the DCC coefficient between Gold and Copper is extremely volatile and it has more positive than negative values, suggesting for any investor a risky correlation. Moreover, DCC coefficient presents two main troughs (2nd March 2009 and 5th August 2011) generated by short-term global market drops of the following economic facts: (a) in 2nd March 2009, Dow Jones Industrial Average fell below 7,000 for the first time since 1997, and (b) in 5th August 2011, when Standard & Poor's credit rating agency downgraded the credit rating of the USA (from AAA to AA+).

Figure 3. Dynamic conditional correlations of the bivariate FIGARCH(1,d,1)-cDCC model



Notes: The red lines illustrate the dynamic conditional correlations (R_t), generated by Equation 6 for all the pairs of markets.

Figure 3 reveals that the DCC coefficient between Gold and Zinc has mainly positive values, although is it extremely volatile over time, indicating a low stability of the correlation. Interestingly, we observe two major extreme troughs over time (15th September 2008 and 5th August 2011) generated by major economic events, i.e. (a) in 15th September 2008, Lehman Brother bankrupted, and (b) when Standard & Poor's credit rating agency downgraded the credit rating of the USA (from AAA to AA+) (5th August 2011).

Figure 3 shows that the DCC coefficient between Gold and Aluminium has mainly positive values, although is it presents extreme volatility over time, indicating a risky correlation for any investor. Additionally, DCC coefficient demonstrates mainly one extreme trough (18th March 2009) and one extreme peak (May 2011) due to the following reasons: (a) in 18th March 2009, Federal Reserve System Chairman Ben Bernanke caped United States Treasury Department yields, and(b) in 2nd May 2011, Osama bin Laden had been killed.

5. Conclusions

This paper investigated the impact of future Gold market on future markets for Silver, Copper, Zinc and Aluminium. Specifically, we quantify volatility transmission by employing a bivariate cDCC-FIGARCH model. The under investigation period is from 2006 until 2011. To the best of our knowledge no empirical study has attempted before to analyze the volatility spillover effects between the under investigation futures markets using our theoretical framework.

We find interesting results. According to the descriptive statistics, future Zinc market returns shows the largest fluctuations compared to the rest future metal markets. Next, we estimate the Jarque-Bera statistic. Results suggest that the daily returns are not distributed normally for all markets. Also, we employ cDCC- FIGARCH(1,d,1) model. Results indicate strong evidence of volatility spillover effects. DCCs analysis state evidence of contagion effects for all the pairs of future metal markets.

A natural extension to this article would be to investigate the potential contagion mechanisms during the period 2011-2019 post global financial crisis. In particular, we focus on the revelation of possible contagion effects between future Gold market and future markets for Silver, Copper, Zinc and Aluminium.

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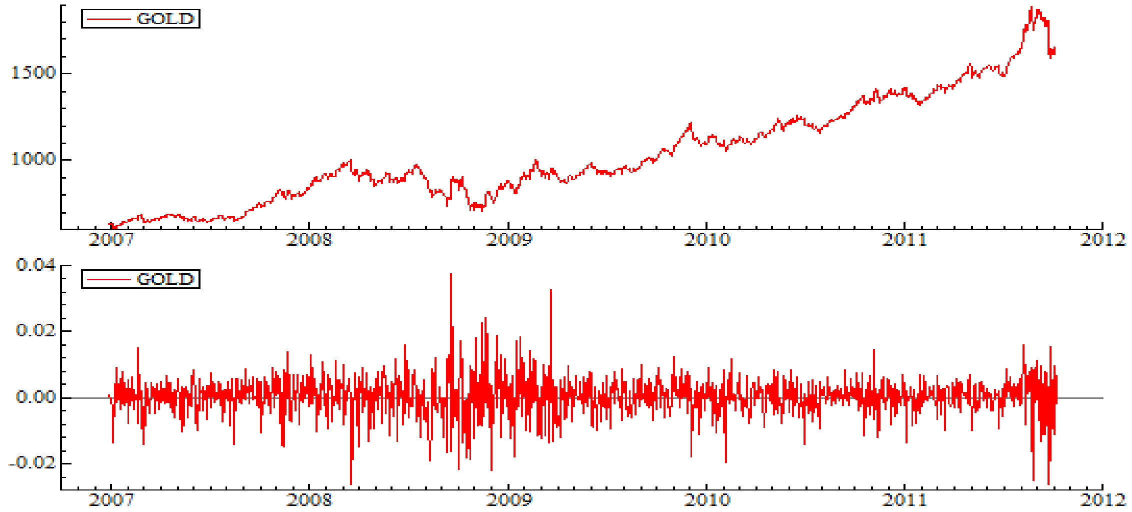
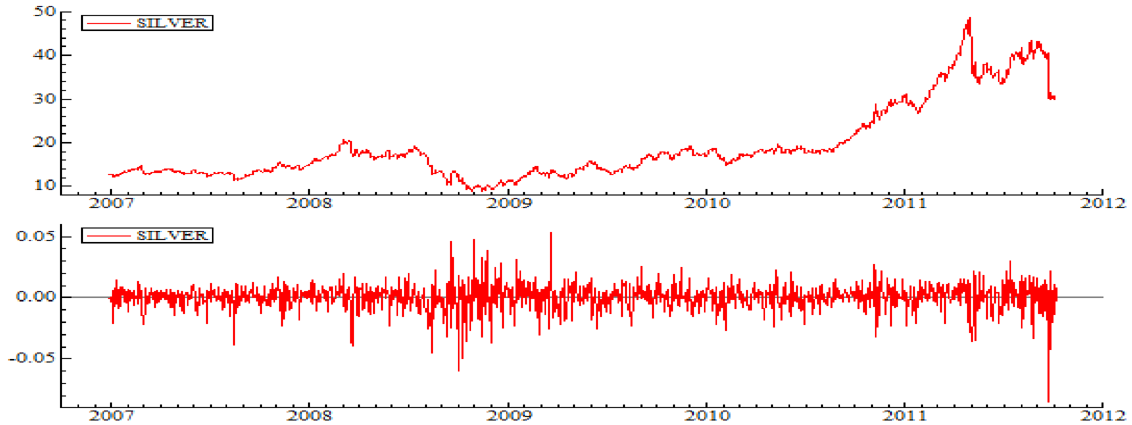
Appendices

Appendix A. Actual series of futures markets and their respective logarithmic returns.

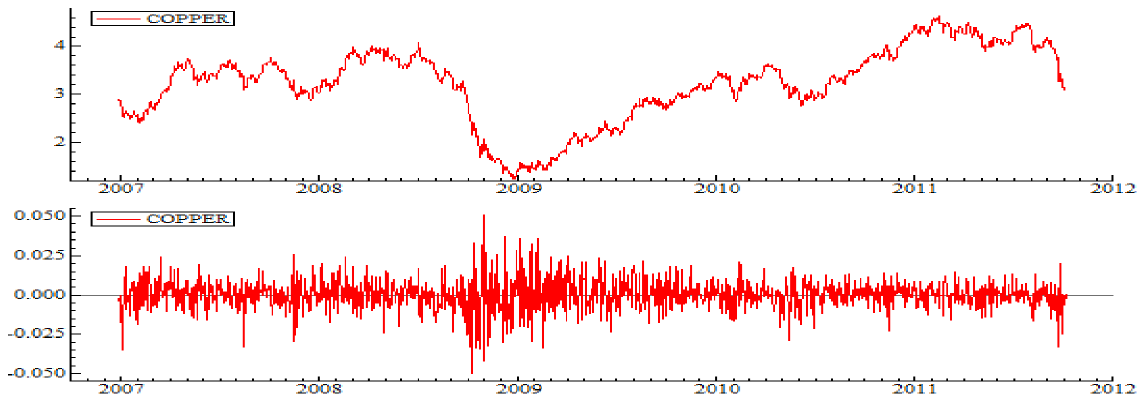
Graph A. Gold



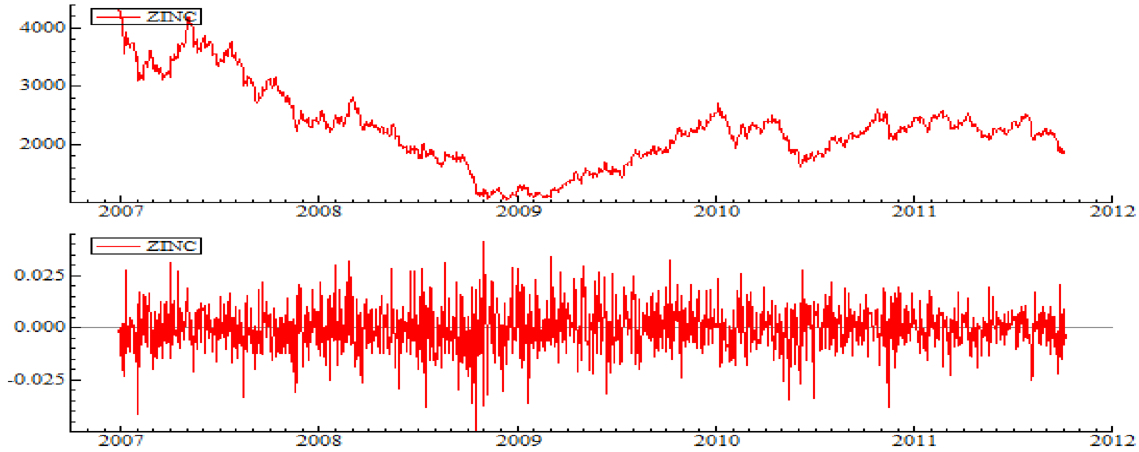
Graph B. Silver



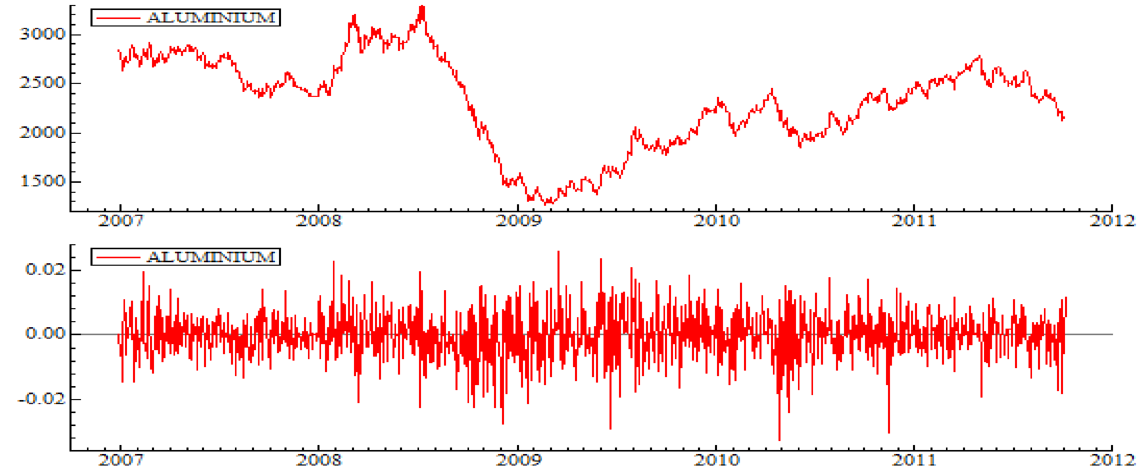
Graph C. Copper



Graph D. Zinc



Graph E. Aluminium



Notes: We calculate futures market returns using the equation: $r_t = log(p_t) - log(p_{t-1})$.