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Asymmetric Momentum Threshold Effect of Copper Futures Returns on Spot Returns Volatility in London Metals Exchange under High Volatility

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Abstract

This paper discusses the asymmetric momentum threshold effect of copper futures returns on spot returns volatility in the London Metal Exchange. Referring the Threshold Autoregressive (TAR) and Momentum Threshold Autoregressive (MTAR) models, this study utilizes a Hybrid MTAR-GARCH model to test the asymmetric momentum threshold effects of LME copper futures returns on spot returns volatility. It is revealed that there are indeed asymmetric momentum threshold effects of LME copper futures returns on spot returns volatility. This finding would be beneficial to financial decision-making concerning copper price hedging, arbitrage and investment amidst high volatility market conditions.

Keywords

Returns, Volatility, Asymmetric Effect, Hybrid MTAR-GARCH

1. Introduction

Copper is a malleable metal with high thermal and electrical conductivity. It is widely used in infrastructure projects such as power electronics, architecture and transportation. As a result, the copper market has become an investment instrument and entity for related industries and financial professionals, and the impact of copper price fluctuations on the global economy is often discussed.

Gao and Wang [1] utilized the asymmetric ARMAX-GARCH model to test basis volatilities and found that London Metal Exchange's (LME) six metal futures contract prices (aluminium, copper, lead, tin, zinc and nickel) and

NYMEX's copper futures price have strong and negative asymmetries, whereas such asymmetries were not revealed in terms of NYMEX's gold and silver futures prices. Zhu *et al.* [2] used the VEC model and ECARCH model and found that the exchange rate of RMB against US dollars, foreign exchange reserves and broad monetary supply exerted short-term influence on three-month copper futures prices of Shanghai (SH), with broad monetary supply exerting long-term influence. Zhang and Tu [3] utilized the ARJI-GARCH model and found that the fluctuations and jumps of international oil prices have a more significant impact on China's copper prices than aluminium prices. Wu and Hu [4] studied the volatility clustering and volatility correlation of China's copper, aluminium and zinc prices and found that the three metals' prices fluctuated substantively and had dynamic correlations during the financial crisis.

Marbrouk [5] utilized five models, namely the Integrated GARCH, GRACH, FIGARCH, FIAPARCH and hyperbolic GARCH models, revealing that LME's copper, aluminium, nickel and zinc prices showed volatility persistence, clustering and asymmetry, and put forth hedging strategies via VAR assessment. Wang and Chang [6] used the VAR model to reveal that house price index (HPI) exerted significant influences on LME copper prices, ISM Purchasing Managers' Index and S&P 500 Index. The above studies mainly focus on the research results of subjects concerning the correlations between copper prices and oil, metals, the overall economic indicators, volatility, etc., instead of discussing fluctuations under high volatility market conditions.

Based on cost of carry principles, the price variance between spots and futures could be regarded as non-equilibrium adjustment conditions. Deduced from Fama and French [7], Gao and Wang [1] found that the impacts of short-term demand caused major metal price changes for spots, rather than for futures. Furthermore, the increase in spots price volatility was larger than that of futures. Chatrath *et al.* [8] found that, under high volatility, lead-lag asymmetry could be observed against index futures and spot markets, where the returns volatilities are positively correlated.

Traditionally, the GJR-GARCH model is used to investigate the asymmetric residual effects on conditional volatility [9] [10] [11] [12] [13]. The shortcoming of such a model is that the model distinguishes asymmetric volatility behaviour based on positive or negative residuals, *i.e.*, using zero as a threshold. However, the zero-threshold model might not be necessarily the most suitable one. Thus, scholars have developed "non-zero-threshold" TAR and MTAR models [14] [15] [16]. Recently, Goo and Shih [17] utilized Hybrid MTAR-GARCH (HMTAR) model to simultaneously observe two random thresholds of residuals and residual differences, and found that, under highly volatile securities market conditions, the basis volatility of index futures did exhibit asymmetric TAR and MTAR phenomena.

By using HMTAR-GARCH model, this study intends to test the asymmetric effects and nonlinear momentum threshold effects of London's copper futures returns on spot returns volatility under highly volatile market conditions. The findings would improve the forecast of copper spot volatility and arbitrage decision-marking under high volatility. The rest of paper is organized as follows. Section 2 describes data and research methodology, including linear and non-linear unit root tests, ARCH effect tests, GJR-GARCH, and HMTAR-GARCH model development and estimation procedure. Section 3 shows the empirical research findings. Section 4 summarizes the conclusion and suggestions.

2. Research Methodology

2.1. The Source of Data

The daily data were London Metal Exchange (LME) copper spots and futures closing prices. The sample period ranges from Jan. 2, 1997 to Dec. 31, 2018. A total of 5605 samples (including from the period of financial crisis) from LME were collected.

Firstly, the returns of the LME copper spots and futures are defined as follows:

$$RET_t = \ln\left(SPR_t / SPR_{t-1}\right) = \ln\left(SPR_t\right) - \ln\left(SPR_{t-1}\right) \tag{1}$$

$$FR_t = \ln\left(FPR_t / FPR_{t-1}\right) = \ln\left(FPR_t\right) - \ln\left(FPR_{t-1}\right) \tag{2}$$

SPR_t represents the copper spot prices at time t, RET_t represents the copper spot returns. FPR_t represents the copper futures prices, FR_t represents the copper futures returns. Referring to the research of Baur and McDermott (2010), the period of financial crisis is defined from Oct. 29, 2007 to Nov. 20, 2008, which is the ending day when the International Monetary Fund (IMF) signed the USD 2.1 billion Economic Stabilization Program with Iceland.

2.2. Unit-Root Test

2.2.1. Augmented Dickey-Fuller (ADF) Unit Root Test

In 1981, Dickey-Fuller [18] suggested to augment the DF unit root test by taking into consideration the serial correlation of residual terms as well as incorporating more previously measured value of error terms as explanatory variables, so that the impacts of the serial correlation of the error terms could be removed, and subsequently carrying out the hypothetical test on "λ" after having assessed the model via OLS.

1) The random walk model without drift or trend components

$$\Delta y_t = \lambda y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

2) The random walk model with drift but no trend component

$$\Delta y_t = \alpha_0 + \lambda y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{4}$$

3) The random walk model with drift and trend components

$$\Delta y_t = \alpha_0 + \gamma_t + \lambda y_{t-1} + \sum\nolimits_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{5}$$

The null hypothesis is $H_0: \lambda = 0$ (there is a unit root, time series data are not stationary).

The alternative hypothesis is $H_1: \lambda \neq 0$ (there is no unit root, time series data are stationary).

2.2.2. Phillips-Perron (PP) Unit Root Test

In 1988, Phillips and Perron [19] utilized the non-parametric statistics of central limit theorem in function forms to simultaneously examine whether the residual terms have autocorrelation and heteroscedasticity. The PP unit root model for testing the random walk model with drift and trend component is as follows:

$$y_t = \alpha + \sigma\left(t - \frac{T}{2}\right) + \varphi y_{t-1} + u_t \tag{6}$$

The null hypothesis is $H_0 = y_{t-1} + u_t$.

Where the α, σ and φ are regression coefficients test when $\alpha = \sigma = 0$ and $\varphi = 1$, if there is a unit root, the time series data are not stationary; otherwise the time series data would be stationary and the null hypothesis would be rejected.

2.2.3. Nonlinear Unit Root Test (KSS Unit Root Test)

ADF and PP unit root tests are based on the assumptions that the series is linear, and therefore excludes the nonlinear series which might cause low statistical power. In light of this, Kapetanios *et al.* [20] put forth the nonlinear structured unit root test, which mainly uses a nonlinear ESTAR model to examine whether the time series data are stationary. The KSS unit root test is as follows:

$$\Delta y_t = \gamma y_{t-1}\left[1 - \exp\left(-\theta y_{t-1}^2\right)\right] + \varepsilon_t \tag{7}$$

The null hypothesis is $H_0: \theta = 0$ (There is a unit root, the time series data are not stationary). Δy_t is the rate of change of parameter coefficient, ε_t is the error term, θ is the conversion rate of ESTAR model. Since γ could not be verified under KSS unit root null hypothesis, the formula (7) is re-calculated using Taylor series expansions. After first asymptotic expansion, the model is as follows:

$$\Delta y_t = \upsilon y_{t-1}^3 + \text{error} \tag{8}$$

In response to the error series correlation, the lagged variable Δy_t is added into the following model:

$$\Delta y_t = \upsilon y_{t-1}^3 + \omega_1 \Delta y_{t-1} + \omega_2 \Delta y_{t-2} + \cdots + \omega_p \Delta y_{t-p} + \text{error} \tag{9}$$

The null hypothesis is $H_0: \upsilon = 0$, there is a unit root, the time series data are not stationary; otherwise the time series data would be stationary, and the null hypothesis would be rejected.

2.2.4. The Conventional TAR and MTAR Models

Enders and Granger [21] and Enders and Siklos [15] incorporated threshold and momentum auto regression to test whether there is a long-term equilibrium. The TAR model is:

$$y_t = \beta_0 + \beta_1 X_t + u_t \tag{10}$$

$$\Delta u_t = I_t \rho_1 u_{t-1} + (1 - I_t) \rho_2 u_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta u_{t-1} + \varepsilon_t \tag{11}$$

where ε_t is white noise, β_0, β_1, ρ_1, ρ_2 and γ_i are regression coefficients, τ is the unknown threshold value simulation:

$$I_t = \begin{cases} 1 & \text{if } u_{t-1} \geq \tau_1 \\ 0 & \text{if } u_{t-1} < \tau_1 \end{cases} \tag{12}$$

MTAR is used to adjust the process. The first residual difference series is:

$$\Delta u_t = M_t \rho_1 u_{t-1} + (1 - M_t) \rho_2 u_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta u_{t-1} + \varepsilon_t \tag{13}$$

$$M_t = \begin{cases} 1 & \text{if } \Delta u_{t-1} \geq \tau_2 \\ 0 & \text{if } \Delta u_{t-1} < \tau_2 \end{cases} \tag{14}$$

The conventional approach uses Formula (11) and (13) to test separately, thus it is unable to simultaneously test two effects. The following section would use the hybrid MTAR-GARCH model to examine when the residuals and differences are lower than thresholds, whether there are asymmetric and nonlinear incremental effects.

2.2.5. The Hybrid MTAR-GARCH Model

Finally, this study refers to the hybrid MTAR-GARCH model adopted by Goo and Shih [17], which proposes the average and variance formula, and takes into account the variable of simulation during the financial crisis. The empirical models are as follows:

$$\begin{aligned} RET_t = {} & \zeta_0 + \zeta_1 RET_{t-1} + \zeta_2 FR_{t-1} + \zeta_3 (I_t FR_{t-1}) + \zeta_4 (M_t FR_{t-1}) \\ & + \zeta_5 (D_1 FR_{t-1}) + \zeta_6 (D_1 I_t FR_{t-1}) + \zeta_7 (D_1 M_t FR_{t-1}) + \varepsilon_t \end{aligned} \tag{15}$$

$$\begin{aligned} h_t = {} & \theta_0 + \nu_1 h_{t-1} + \theta_1 \varepsilon_{t-1}^2 + \eta_1 FR_{t-1} + \eta_2 (I_t FR_{t-1}) + \eta_3 (M_t FR_{t-1}) \\ & + \eta_4 D_1 FR_{t-1} + \eta_5 (D_1 I_t FR_{t-1}) + \eta_6 (D_1 M_t FR_{t-1}) \end{aligned} \tag{16}$$

where,

$$I_t = \begin{cases} 1 & \text{if } \varepsilon_{t-1} \geq \tau_1 \\ 0 & \text{if } \varepsilon_{t-1} < \tau_1 \end{cases} \tag{17}$$

$$M_t = \begin{cases} 1 & \text{if } \Delta \varepsilon_{t-1} \geq \tau_2 \\ 0 & \text{if } \Delta \varepsilon_{t-1} < \tau_2 \end{cases} \tag{18}$$

where RET_t is the copper spot returns, FR_{t-1} is the copper futures returns, D_1 is the variable of simulation during the financial crisis. Coefficients η_2 and η_5 test whether the residuals have positive or negative asymmetric TAR effect; coefficients η_3 and η_6 test whether the residual differences have a nonlinear MTAR effect. The residual term ε_t does not have autocorrelation and has white noise feature. Moreover, when $\tau_1 = \tau_2 = 0$, Models (15) and (16) are similar to the GJR-GARCH model.

2.2.6. Research Hypotheses

When a stock market is under overwhelming sell-off pressure (*i.e.* under high volatility), short-term futures would be under higher pressure to sell, and traders could sell the futures prior to the upcoming stock price drop. As a result of the increasing pressure to sell short-term futures, the futures prices would drop more rapidly, leading to augmented price fluctuations. Speculators and arbitrage investors could sell spots and buy futures to obtain additional premiums.

Therefore, if the previous residuals (ε_{t-1}) are lower than certain thresholds, it suggests that the rate of futures price drops was faster than expected and caused the following trading day to have larger volatility; and if the previous residual differences ($\Delta\varepsilon_{t-1}$) are lower than certain thresholds, it reveals that the market is becoming highly unexpected, volatility is likely to increase even more. This study refers to the assertions of Gao and Wang [1] and Goo and Shih [17], exploring whether the London Metal Exchange's copper spots and futures, would experience the same trends as in the stock market under high volatility. Therefore, this study examines the following hypotheses:

Hypothesis 1: During the Financial crisis, when the pre-Financial crisis residual is lower than its threshold τ_1, the impact of future returns on spots volatility is greater (The TAR effect, *i.e.*, $\eta_5 < 0$).

Hypothesis 2: In the financial crisis period, when the pre-financial crisis residual difference is lower than the momentum threshold τ_2, the impact of future returns on spots volatility is greater (The MTAR effect, *i.e.*, $\eta_6 < 0$).

Hypothesis 3: The MTAR effect has a greater negative impact compared to the TAR effect during volatile market condition, *i.e.*, $H_{3\text{-}1}: \eta_6 < \eta_5$. Another way to verify the hypothesis is to include non-volatile period, *i.e.*,

$H_{3\text{-}2}: \eta_3 + \eta_6 < \eta_2 + \eta_5$.

3. The Results of Empirical Research

In Baur and McDermott's [22] study, the financial crisis starting from October 29, 2007 and ending on November 20, 2008. The sample period of this study is from Jan. 2, 1997 to Dec. 31, 2018. A total of 5604 samples were been collected from LME concerning the spot and futures returns on a daily basis (including the data from the financial crisis that lasts 270 days) as shown in **Table 1**.

The descriptive statistical summary of futures returns (FR) is shown in **Table 2**.

Compared to other periods, FR has a larger standard deviation during the Financial crisis, with a negative average returns. Then, the ADF, PP and KSS unit root tests on RET series are examined. In **Table 3**, *the results show that the series are stationary regardless of lags* 5, 10 *or* 20. *As shown in* **Table 4**, *the heteroscedasticity test shows that there exist ARCH effects regardless of lags* 1, 5 *and* 10.

The study then adopts a 3-tier computational model. Model 1 is the ARCH model without threshold. Model 2 is the *GJR-GARCH* (1, 1) *model with the TAR threshold* (τ_1) *and the MTAR threshold* (τ_2) *set as* 0. *Model* 3 *is the HMTAR model with random* τ_1 *and* τ_2. *The goodness of fit test of the models* *adopts AIC principles* [23], SBC principles [24] and Log Likelihood function (LL), when the AIC and SBC test results are smaller, the LL results are larger, it suggests that the independent variables of the model are able to explain the dependent variables. Based on the statistical results of the 3-tier computational model, the HMTAR-GARCH model has good model fit, the GARCH model has a slightly less goodness of fit, confirming that the HMTAR-GARCH model is a better fit than other models (**Table 5**).

Hypothesis 1 and Hypothesis 2 are supported, since η_5 and η_6 are negative significantly. The WALD tests show that the null hypothesis $H_{3\text{-}1}:\eta_6<\eta_5$, Chi-square = 0.67915 ($p$ = 0.4099) fails to reach the significant level; while the null hypothesis $H_{3\text{-}2}:(\eta_3+\eta_6)<(\eta_2+\eta_5)$, Chi-square = 4.5936 ($p$ = 0.0321) reaches the significant level. Hence Hypothesis 3 is supported.

Table 1. Segmented period from January 2, 1997 to December 31, 2018.

	Period	Trading Days
Pre-Financial Crisis	January 2, 1997-October 26, 2007	2779
Financial Crisis	October 29, 2007-November 20, 2008	270
Post-Financial Crisis	November 21, 2008-December 31, 2018	2555
Overall Observed Time	January 2, 1997-December 31, 2018	5604

Table 2. The descriptive statistics of copper futures returns (FR).

	Mean	Standard Deviation	Minimum	Maximum
Pre-Financial Tsunami	0.002	0.644	−4.961	4.77
Financial Tsunami	−0.124	1.14	−4.517	5.16
Post-Financial Tsunami	0.009	0.682	−3.406	3.882
Overall Observed Time	0.694	0.008	−4.961	5.16

Table 3. The results of linear and nonlinear unit root tests.

lags	ADF	PP	KSS
	t-Statistic	t-Statistic	t-Statistic
5	−80.2347***	−80.2347***	−14.1395***
10	−21.1022***	−80.1512***	−10.8130***
20	−14.6596***	−80.0157***	−8.7144***

Notes: *, ** and *** indicate 10%, 5% and 1% significant level.

Table 4. The results of heteroscedasticity tests.

Heteroscedasticity Test(lags)	F-Statistic Test	Chi-Square Test
ARCH(1)	430.1581 ***	399.6207 ***
ARCH(5)	199.369 ***	846.9598 ***
ARCH(10)	120.7771 ***	994.9198 ***

Notes: *, ** and *** indicate 10%, 5% and 1% significant levels.

Table 5. 3-tier computational results (5604 obs.).

RET	Model 1		Model 2		Model 3	
	(ARCH)		(GJR-GARCH)		(HMTAR-GARCH)	
	(No Threshold)		($\tau_1 = \tau_2 = 0$)		($\tau_1 = -1.4202; \tau_2 = 1.1655$)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Mean Equation:						
ζ_0	0.0041	0.5877	0.0044	0.6355	0.0049	0.7071
ζ_1	−0.4212	−26.7077 ***	−0.4232	−26.9314 ***	−0.4093	−26.0514 ***
ζ_2	0.5819	38.8885 ***	0.5904	30.0805 ***	0.4208	5.662 ***
ζ_3	−0.2164	−3.4728 ***	0.0094	0.3615	0.1793	2.4352 **
ζ_4			−0.0309	−1.1802	−0.2639	−4.8958 ***
ζ_5			0.0322	0.5865	0.0164	0.2747
ζ_6			−0.0792	−0.6917	−0.2375	−2.9419 ***
ζ_7			−0.1343	−1.1317	0.2789	1.6334 *
Variance Equation:						
θ_0	0.0025	5.5391 ***	0.0025	5.4008 ***	0.002	4.8943 ***
ν_1	0.9405	217.289 ***	0.9412	211.21 ***	0.9466	235.8294 ***
θ_1	0.053	13.6055 ***	0.0525	13.2126 ***	0.0488	13.2596 ***
η_1	−0.0014	−0.6734	−0.0040	−1.1717	−0.1201	−4.5597 ***
η_2	−0.0646	−3.4636 ***	−0.0025	−0.4837	0.119	4.5505 ***
η_3			0.0089	1.3767 *	−0.0012	−0.0748
η_4			−0.0242	−0.7131	0.0321	0.7343
$\eta_5\ (H_1)$			−0.0814	−1.2785	−0.0668	−1.9357 **
$\eta_6\ (H_2)$			0.0297	0.6768	−0.1366	−1.6298 *
AIC	−516.4206		−498.8721		−553.2718	
SBC	−525.7901		−524.2416		−578.6419	
LL	267.2103		266.436		293.6359	

Notes: *, ** and *** indicate 10%, 5% and 1% significant level.

4. Conclusion and Discussion

Recent research mostly focuses on the correlation between LME's copper prices with oil, metals, overall economic indicators and price volatility. For example, Gao and Wang [1] studied the LME's copper futures contract price and NYMEX's copper futures prices and found strong and negative asymmetries. Mabrouk [5] studied the persistence, clustering and asymmetry of LME's copper prices, and the result is consistent with the results of this study, where this study used ARCH model to examine the asymmetric effects of LME's copper futures returns on spot returns volatility. That said, discussions of volatility under highly volatile market conditions are nevertheless absent.

This paper integrates the TAR and MTAR GARCH model as the Hybrid TAR/MTAR-GARCH model to forecast the volatility of copper returns. Meanwhile, it introduces the assessment on the simulated interaction of TAR and MTAR into average and variance formulas so as to prevent the econometrics model from generating errors. Then, it designs two random threshold values to augment the testing method of GJR-GARCH model with zero-threshold value, enabling the variance formula to test two random threshold values simultaneously.

By estimating the asymmetric threshold parameter, it is revealed that the HMTAR-GARCH model has higher explanatory power than the GJR-GARCH model. This study verifies three hypotheses. Firstly, it verifies that during highly volatile period, when the lagged residuals are lower than their thresholds, the impacts on copper returns volatility are greater. Secondly, it verifies that during highly volatile period, when the lagged residual differences are lower than momentum thresholds, the impacts on copper returns volatility are greater. Finally, results show that during highly volatile period, the MTAR effect is even greater than the TAR effect.

In conclusion, the above findings suggest that the Hybrid HMTAR-GARCH model has better level of fitness than the GJR-GARCH model, and the former is able to capture the asymmetric and nonlinear nature of copper returns volatility. In particular, it reveals the asymmetric and nonlinear momentum threshold effects of London's copper futures returns on spot returns volatility under highly volatile market conditions; hence it could facilitate the forecasting of copper spots volatility and arbitrage decision-making during a period of high volatility.

Moreover, in terms of supply and demand of copper, the HMTAR-GARCH model could help clients and suppliers set up better risk prevention strategies and obtain additional earnings from financial practices on top of operating profits. For example, global electricity and electronics sector, architectural sector, transportation industry, industrial manufacturing, retail and consumers, copper mining, copper recycling professionals and governments' infrastructure administrative departments could apply the HMTAR-GARCH model to risk management, thus enable traders and manufacturers to develop better investment and risk prevention strategies.

Although this paper attempts to derive a better threshold GARCH model for exploring better volatility forecasting model, there are some possible modifications. Firstly, the double thresholds model could be extended to multiple thresholds in mean and variance equations. Secondly, the discrete threshold model could be extended to continuous ESTAR or LSTAR-type model, which could measure continuous unexpected information threshold shocks to conditional volatility.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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