2 CONTAGION BETWEEN GOLD AND OTHER COMMODITY GOODS USING BAYESIAN MULTIVARIATE QUANTILE_ON_QUANTILE APPROACH

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Abstract

This study revisits Gold, Nickel, oil price, Copper, and Tin links using Bayesian Multivariate Quantile_on_Quantile approach over the period of 1960M1 to 2022M5. Where the GARCH (1,1) is considered when estimating the model to alleviate the heteroskedastic problem. Our findings show that the connections between Gold returns and other four commodity goods returns change across various quantiles. The GARCH model shows that previous information and persistence gauges vary with current conditional variance under different quantiles. Moreover, the half-life of a shock ranges from 0.38 to 3.72 months for all our markets, which was not found in the existing papers. Our findings provide prominent economic implications for investors, practitioners, and government.

Keywords: Bayesian; Quantile_on_Quantile; Gold; Commodity Goods; GARCH

JEL classification: C11; C21; G10

1. Introduction

As we know the financial liberalization of commodities has rapidly grown with the world market integration over the past two decades. Accompanied by several major market crashes or financial crisis events outbreaks, the behaviour of the price of different commodities becomes further unpredictable. Hence, exploring the linkages among the metals and other commodities provides an important implication for the policy makers (Dutta et al. 2019; Kocaarslan and Soytas 2019; Ghabri et al. 2021; Ren et al. 2022a).

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Several previous papers inspected the linkages among the different assets, where the connection among the gold and oil or other commodities attracted the attention from the practitioners and government (Musibau et al. 2021). For example, the performance of the industrial firm be influenced by the variation of price of the oil and the metals. The volatility of the price for these commodities major resulted from the joint consumption (Shammugam et al. 2019). In addition, the shocks of the precious metal, gold, could impact the wealth of the firms, investors, and government. Especially, the response to the market turmoil further interrupts the behavior of the commodities (Bouri et al. 2021; Shahzad et al. 2021).

Thereby, utilizing the linkages among the commodities to hedgy the uncertainty of the price movement seemly can protect the investors from the unexpected loss. In other words, the volatility contagion effect between commodities is the deterministic factor while implementing the hedgy strategies.[4]

Insofar, a lot of literatures investigated the connectedness between oil and gold or other metals (e.g., Behmiri and Mangera 2015; Balcilar et al. 2019; Rehman et al. 2020; Mensi et al. 2021). The results of these papers accordingly show that the connection between oil and gold or other metals are time-varying. These could be supported by the assertion of Tang and Xiong (2012). Specifically, the volatility pattern of commodity investment may be disturbed in the future because of the innovation of the commodity markets.

The above mentioned papers consider the association between the stock market and gold, oil or other metals, or the oil and other metals, indicating that the hedgy strategies could only be practiced between them. In terms of the linkage between gold and other metals or oil, it also provides important implication for the decision makers. However, papers exploring this issue are few, therefore, this study intends to investigate the contagion effect between gold and other metals and oil individually, the first purpose in this study.

To precisely interpret the linkages between the commodities of interest, some novel econometric approaches were proposed and implemented in preceding research. For instance, using the nonlinear Granger causality test and nonlinear ARDL test, proposed by Hiemstra and Jones (1994), Kumar (2017) examined the causality between oil and Gold prices in the Indian market. Chang and Fang (2022) employed the ARDL to examine the nexus among different assets by using the granger causality. Besides, from the perspective of the volatility models, Morema and Bonga-Bonga (2020) explored the influencing extent of the Gold and oil price volatility on South African stock markets by using the VAR-ADCC-GARCH model.

Moreover, by introducing the time-varying property in the VAR model (e.g., Antonakakis et al. 2015; Diebold and Yilmaz 2015; Mokni et al. 2020), the time-varying characteristics among different assets, especially in stock markets, are also obtained. On one hand, the Spectrum analysis aspect was also used to scrutinize the different time-frequency nexuses between the commodities of interest. Shahzad *et al*. (2022) following Mo et al. (2019), choose the Wavelet Power Spectrum Analysis to inspect the variation of volatility of Bloomberg commodity index (BCOM) and WTI crude oil (CRUDE) prices at different time scales. A similar approach was also implemented in preceding studies (Jiang et al. 2020).

Finally, since Koenker and Bassett (1978) propose quantile regression, this econometric approach was also used to detect the nexus among these commodities of interest. For example, Dawar et al. (2021) explore the linkage between energy stock price and crude oil by using quantile regression. Following the Koenker and Bassett (1978), Sim and Zhou (2015) propose an alternative approach, the Quantile_on_Quantile method, to subtly capture the connection between the dependent and independent variables across different quantiles, which further detailly sketches the contagion effect. Caporin et al. (2021) extend the Caporin et al. (2018) and

[4]. *For further detail, please see Tiwari and Sahadudheen 2015 and Jain and Biswal 2016.*

Sim and Zhou (2015) to consider the GARCH effect in the Quantile_on_Quantile scheme to deal with the heterogenous effect of the time series data. To deeply explore the linkage among the oil and other metals across vary quantile, we follow Caporin et al. (2021) to examine the contagion effect, which is the second purpose.

Our empirical results are shown as follows. First, the connectedness between Gold and various mineral assets provides different patterns. However, by examining the extreme pattern of the connection between these assets, the positive spillover effect is demonstrated in the WTI and Copper; the negative contagion effect is obtained in Tin, while Nickels exhibits asymmetric spillover effect, suggesting that the linkages between Gold and other commodities are different. Second, the maximum and respective minimum number of months of the half-life of a shock is aproximately 3.072 months at the (0.05 and 0.6) quantiles and about 0.38 months at the (0.15 and 0.95) quantiles, respectively. In addition, considering the QQ coefficients of the current conditional variance (σ_t^2) and previous information (e_{t-1}^2), we also find that previous information influences the change in current conditional variance by quantiles.

Based on these findings, some contributions of this study are summarized as follows. First, in relation to preceding studies showing that the connections between Gold and WTI and Gold and other metals are time-varying and non-manifest (Behmiri and Mangera 2015; Balcilar et al. 2019; Rehman et al. 2020; Mensi et al. 2021), this paper not only clearly captures the connectedness between Gold and WTI, and Gold and other metals, but also incorporates the time series behavior of Gold and other examined assets by employing the Quantile_on_Quantile with GARCH effect. Second, this study also provides the economically and statistically significance results, that is, the maximum half-life of an impact is about 3.072 months at the quantiles (0.05 and 0.6) and the minimum half-life of an impact is about 0.38 months at the quantiles (0.15 and 0.95). Compared with the previous study, we apparently emphasize the impact effect more precisely under different market conditions.

The remainder of this study is organized as follows: the second section presents the review of literature. The model and data and empirical results are described in the third, fourth, and fifth sections, respectively. The final section presents conclusions,

2. Review of Literature

A great deal of the preceding studies explore the linkages among commodities (Bampinas and Panagiotideis 2015; Balcilar et al. 2019; Bassil et al. 2019; Tiwari and Sahadudheen 2015; Jain and Biswal 2016; Shahbaz et al. 2017). For example, Bampinas and Panagiotideis (2015) focus on the connection between the global oil market and Gold spot prices during the pre and post global financial crisis. The authors show that causality not only is linear, but is also unidirectional from oil to Gold during the pre-crisis period, and bidirectional nonlinear causality linkages are present after the market turmoil. However, Balcilar et al. (2019) apply time-varying causality test to inspect the links between Gold and oil and find that the connection between both exist the time-variation. Bassil et al. (2019) also examine the long-term interaction between the Gold and oil and find that there is time-variation in the connectedness. In addition, volatile price behaviour for these commodities is induced by the joint consumption (Shammugam et al. 2019). Therefore, understanding the linkages between Gold and oil could help investors to efficiently implement the hedge strategies (Mensi et al. 2021).

Additionally, research on the linkages between Gold and Copper is also examined by a lot of previous literatures. For instance, Zhang and Tu (2016) contend that shocks on the oil price could largely impact the price of Gold and Copper. An et al. (2020a) examine the volatility contagion effects among the oil, Gold and Copper and show that there are some contagion effects exhibited in these assets. Rehman et al. (2020) and Rehman et al. (2021) assert that efficiently allocating the crude, oil, and Copper may help the investors enjoy the diversification benefit.

Moreover, Tang and Xiong (2012) contend that the financialization of the commodities gradually innovates. The categories of the metals which can be traded on the financial markets have been increasing. Additionally, they were accompanied by the increasing demands for Nickel due to the innovation of the electricity vehicle battery. Examining the links between Nickel and oil also occupy an inevitable role. For example, Plourde and Watkins (1998) examine the volatility of the crude and many metals such as Copper, Nickel, and so on and point out that higher volatile exists in the shocks on the oil than in the metals. Behmiri and Mangera (2015) examine the potential influence of oil prices impact on the price volatility of several metals, including Aluminum, Copper, Gold, Lead, Nickel, Palladium, Platinum, Silver, Tin, and Zinc. Their results show that the response of the metal price volatility to oil prices shocks is different and asymmetric among them. Hence, based on these papers, disentangling the connection between Gold and other commodities is an important issue. However the papers exploring the contagion effect between Gold and Nickel, Copper, crude oil, Tin simultaneously are few. Therefore, the first purpose of this study is to capture and discuss the interrelation among these commodities.

To address a sequential problem of examination of the linkage between the assets of interest. (the verb is missing!) Three aspects of the econometric approaches are used in the previous research. Following Hiemstra and Jones (1994), Kumar (2017) exploits two nonlinear approaches, including the Granger causality and ARDL test, to verify the causal effect between oil and Gold prices in the Indian market and finds a bidirectional nonlinear linkage between oil and Gold prices and that the positive shock of oil price on Gold price is further apparent than negative interruptions. Chang and Fang (2022) exploit the ARDL to test the nexuses and implement the granger causality test to detect the casualty linkage among the different asset classes. The empirical results reveal that natural resources commodities indices (crude oil, precious metals, livestock, and agriculture products) have a positive connection with stock market indices in China. Morema and Bonga-Bonga (2020) explore the influencing extent of the Gold and oil price volatility on South African stock markets by using the VAR-ADCC-GARCH model. Their results verify that the volatility contagion effect is present between Gold and stock markets, oil and stock markets. These papers consider the non-linear model or volatility models to sketch out the interacting patterns among the assets of interest.

Unlike the noted above method, the time-varying parameter vector autoregressive (TVP-VAR) model is used in some studies. Antonakakis et al. (2015) study the dynamic linkages between the business and financial cycles in the G7 countries. Diebold and Yilmaz (2015) analyze the connectedness of stock return volatility between the American and European financial institutions during the 2004-2014. In term of the nexus among the commodities, Mokni et al. (2020) show that a weak average of the total dynamic relationships between oil price shock and Gold returns is found during the stable period, however, it become more intense during the market crash period by exploring the dynamic connections between three identified structural oil price shocks and Gold prices.

Moreover, other studies utilize the Spectrum viewpoint model to disentangle the varying time-frequency connection between the assets of interest. Where, the wavelet approach usually be exploited in the economic and finance fields. For example, based on the Mo et al. (2019), Shahzad et al. (2022) apply the Wavelet Power Spectrum Analysis to examine the variation of volatility of Bloomberg commodity index (BCOM) and WTI crude oil (CRUDE) prices at different time scales. The authors show that average level volatility of BCOM and CRUDE vary by different time frequencies. Similar application of the wavelet analysis is also used in preceding studies (See, Jiang et al. 2020). Different from noted above, this approach would distinguish different time dominance between the assets of interest. Hence, those who intend to capture the different time-scale connection among the assets can employ these models.

However, the above mentioned papers consider either the long- and short-term return and volatility nexus or varying time-dominance approach. Reviewing past literatures, different from aforementioned methods, some studies examine the connectedness by using the quantile regression, proposed by Koenker and Bassett (1978). For example, Dawar et al. (2021) examine the connection between energy stock price and crude oil by using quantile regression. Nevertheless, a drawback of the quantile regression is revealed, that is only the connection between the different quantiles of depend variable and the independent variables is obtanied, thus Sim and Zhou (2015) propose an alternative approach, the Quantile_on_Quantile method. Thereafter, Caporin et al. (2021) further incorporate the GARCH effect in the Quantile_on_Quantile scheme to deal with the heterogeneous effect of the time series data. Hence, this study intends to implement a series analysis by following the Caporin et al. (2021) and also investigate the volatility process among these commodities (i.e. using the half-life time and the volatility 3-D plots). In this regard, this is the second main issue examined in this study.

3. The Model – Bayesian Multivariate Quantile on Quantile Approach

Extending the method in Sim and Zhou (2015), this study to examine the comprehensive relationship between Gold and the other four commodity goods (Nickel, Copper, Tin, and Oil price). Different from general quantile regression, this approach further detailly captures the various quantile connections between the dependent and independent variables by applying the non-parametric estimation. To examine the impact of different quantiles of commodity goods on the various quantiles of Gold by using the following nonparametric multivariate Quantile_on_Quantile regression model. The related definition of the variables and the corresponding model are shown in the following.

$$Gold_t = \beta 1^{\theta}(Nickel_t) + \beta 2^{\theta}(Copper_t) + \beta 3^{\theta}(Tin_t) + \beta 4^{\theta}(OILP_t) \quad + \quad W(Gold_{t-1}) + u_t^{\theta} \tag{1}$$

The equation (1) can simply be elicited as the equation (2):

$$Gold_t = \beta i^{\theta}(X_{it}) + W(Gold_{t-1}) + u_t^{\theta} \tag{2}$$

Aiming to mitigating the series correlation inducing the inconsistence problem, the autoregressive term, $Gold_{t-1}$, is added into equation (2). u_t^{θ} is the error term of the model. Additionally, $\beta i^{\theta}(*)$ is the coefficients that describe the relationship between the $Gold_t$ and four commodities said ($X_{it} = Nickel, Copper, Tin, OIL$). This model accounts the different quantiles impact of the X_{it} across the entire distribution of the $Gold_t$. However, the true $\beta i^{\theta}(*)$ cannot be obtained, owing to the information between the $Gold_t$ and X_{it} is insufficient. Therefore, the estimator is approximated by a first-order Taylor expansion around a quantile ${X_{it}}^{\tau}$, such that

$$\beta i^{\theta}(X_{it}) = \beta i^{\theta}({X_{it}}^{\tau}) + \beta i^{\theta'}({X_{it}}^{\tau})(X_{it} - {X_{it}}^{\tau}) \tag{3}$$

where $\beta i^{\theta'}$ is the partial derivative of $\beta i^{\theta}(X_{it})$ with respect to X_{it}, dubbed the marginal effect. The important characteristic of Eq. (3) is that two doubly index terms, including θ and τ, are considered in the coefficients $\beta i^{\theta}({X_{it}}^{\tau})$ and $\beta i^{\theta'}({X_{it}}^{\tau})$. Given that $\beta i^{\theta}({X_{it}}^{\tau})$ and $\beta i^{\theta'}({X_{it}}^{\tau})$ are functions of θ and X_{it}, while X_{it} is a function of τ, it is obvious that $\beta i^{\theta}({X_{it}}^{\tau})$ and $\beta i^{\theta'}({X_{it}}^{\tau})$ are both functions of θ and τ. Besides, $\beta i^{\theta}({X_{it}}^{\tau})$ and $\beta i^{\theta'}({X_{it}}^{\tau})$ could be regarded as $\beta_0(\theta, \tau)$ and $\beta_{1i}(\theta, \tau)$, respectively. Consistently, Eq. (2) could be rewritten as

$$\beta i^{\theta}(X_{it}) \approx \beta_0(\theta, \tau) + \beta_{1i}(\theta, \tau)(X_{it} - {X_{it}}^{\tau}) \tag{4}$$

Putting the Eq. (4) into Eq. (2), we obtain the Eq. (5):

$$Gold_t = \beta_0(\theta,\tau) + \beta_{1i}(\theta,\tau)(X_{it} - X_{it}{}^{\tau}) + W(Gold_{t-1}) + u_t^{\theta} \quad (5)$$

This part of $\beta_0(\theta,\tau) + \beta_{1i}(\theta,\tau)(X_{it} - X_{it}{}^{\tau}) + u_t^{\theta}$, in Eq. (5) is the θth conditional quantile of $Gold_t$. The connection across various quantiles between the dependent and independent variables can be obtained, due to the parameters β_0 and β_{1i} are doubly indexed in θ and τ. Therefore, Eq. (5) estimates the overall dependence structure between $Gold_t$, and their respective distributions. Estimating Eq. (5) requires replacing X_{it} *and* $X_{it}{}^{\tau}$ with their estimated counterparts $\widehat{X_{it}}$ *and* $\widehat{X_{it}}{}^{\tau}$, respectively. The estimates of the parameters b_0 and b_1, which are the estimates of β_0 and β_{1i}, are obtained by solving the following minimization problem:

$$\min_{b_0,\, b_{1i}} \sum_{i=1}^{n} \rho_\theta\left[Gold_t - b_0 - b_{1i}\left(\hat{X}_{it} - \widehat{X_{it}}{}^{\tau}\right) - w(Gold_{t-1})\right] * K\left(\frac{F_n(\hat{X}_{it}-\tau)}{h}\right) \quad (6)$$

Where $\rho_\theta(\mathrm{u})$ is the quantile loss function, defined as $\rho_\theta(\mathrm{u}) = \mathrm{u}(\theta - \mathrm{I}(\mathrm{u} < 0))$ and $\mathrm{I}(\cdot)$ is the indicator function. K(*) denotes the kernel function and h is the bandwidth parameter of the kernel.[5] We follow Sim and Zhou (2015) to select a bandwidth parameter h = 0.05 in the current study. To further deal with heteroskedastic problem in residuals we incorporate Quantile_on_Quantile GARCH(1,1) equation into our model and they are as the follow:

$$\sigma_t^2 = \alpha_0 + \alpha_1(\theta,\tau)e_{t-1}^2 + \gamma_1(\theta,\tau)\sigma_{t-1}^2 \quad (7)$$

Here $\sigma_t^2$is conditional variance, e_{t-1}^2 is lag one of the squared residuals to capture the prior information (α_1) , and $\sigma_{t-1}^2$is lag one period of conditional variance that we can apply to estimate the half-life of shock = log(γ_1) / log(0.5).

To the best of our knowledge, this is the first paper to study contagion across commodity goods markets surrounding the extreme events of the two times oil shocks (1974-1976 and 1979-1981), the US stock price crash (1987), Asia financial crisis (1997), global financial crisis (2008), European sovereign debt crisis (2011-2012), and COVID-19 pandemic (2019~current), based on a QQ approach controlling for various types of biases due to omitted variables and endogeneity. We can consider our model as an extension of the quantile-GARCH approach of Caporin et al. (2018) and Caporin et al. (2021).

4. Data

Table 1 reports the descriptive statistic of Copper, Gold, Nickel, Tin and WTI (i.e., oil), price over the period of 1960M1-2022M5. Average price for the Copper, Gold, Nickel, Tin and WTI is 064.103, 519.363, 8812.03, 10,666.02, and 31.673, respectively, and the standard deviation of the corresponding metals is 2,466.673, 508.482, 7,372.352, 16,122.62, and 28.656, respectively. In addition, the empirical results from the Jarque-Bera test show that the distribution of all metals are significant, indicating that the price distribution of these assets does not follow the normal distribution.

We plot these five metal prices (in log form) at Figure 1. From Figure 1 we find several upward and downward patterns, which correspond to several major events like those of two-time oil price shocks (1964-1966 and 1979-1981), stock crisis of 1987 in the USA, 1997 Asian financial crisis,

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[5]. *Regarding kernel function, the Gaussian kernel is used to weight the observations about* $X_{it}{}^{\tau}$. *Two features of this function are symmetrical surrounding to zero and given low weights to the outlier. In this study, these weights are adversely connected to the distance between the empirical distribution function of* $\hat{X}_{it}$, *defined by* $F_n(\hat{X}_{it}) = \frac{1}{n}\sum_{k=1}^{n} I(\hat{X}_{ik} < \hat{X}_{it})$, *and the value of the distribution function that corresponds to the quantile* $X_{it}{}^{\tau}$,*—denoted by* τ.

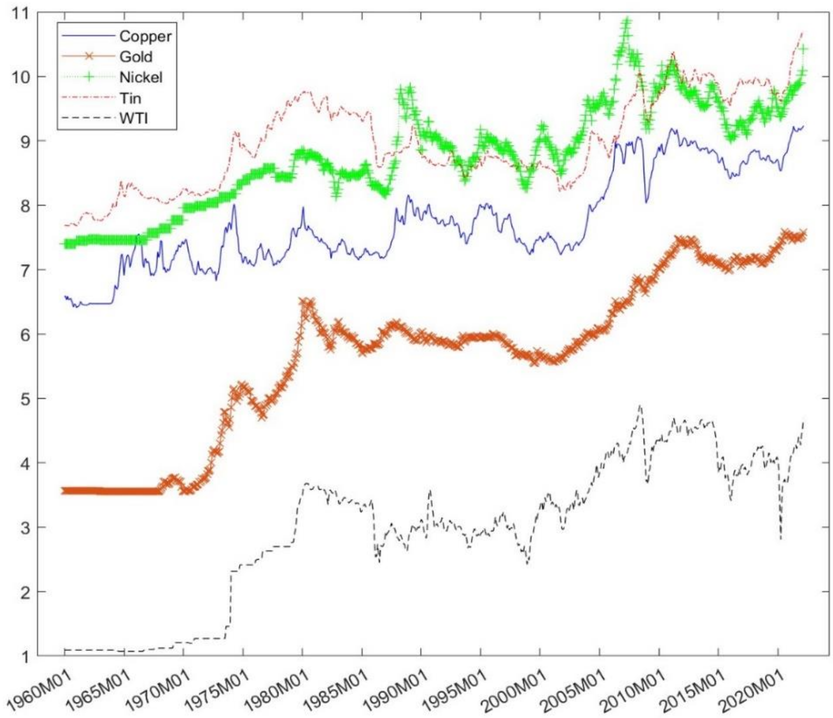
2008-2009 global financial crisis, 2011-2012 European debt crisis and 2019-2021 COVID-19 pandemic crisis.

Table 1. Descriptive Statistics

	Copper	*Gold*	*Nickel*	*Tin*	*WTI*
Mean	3064.103	519.363	8812.030	10666.02	31.673
Median	1877.900	363.340	6391.000	6829.400	21.350
Maximum	10230.89	1968.630	52179.05	402599.0	133.930
Minimum	606.710	34.940	1631.000	2162.700	2.920
Std. Dev.	2466.673	508.482	7372.352	16122.62	28.656
Skewness	1.205	1.212	1.901690	19.3269	1.174
Kurtosis	3.128	3.325	8.091461	467.705	3.609
Jarque-Bera	181.892***	186.838***	1260.463***	6786110***	183.725***
Probability	0.000	0.000	0.000	0.000	0.000

*Notes: ***, ** and * indicate significance at the 1, 5 and 10 % levels, separately.*

Figure 1. Plots of Copper, Gold, Nickel, Tin and WTI



5. Empirical Results and Policy Implication

5.1. Results from Unit Root Tests

To avoid the spurious regression, caused by the non-stationary time-series data, three general unit root tests, including the ADF, PP, and KPSS, are used to examine whether our data is stationary. According to the results, five metals reveal the insignificant evidence for the ADF and PP, but significant at 1% for KPSS, implying that the original time-series data for five metals is non-stationary. Therefore, applying the first-order difference for each series, we find that the results of the ADF and PP are the significance and those of KPSS are insignificance, suggesting the stationary series can be used after first order difference for our price series. Thus, this study decides to use the return for these metals to scrutinize the linkages between Gold and other four commodity goods (like those of Copper, Nickel, Tin and WTI).

Table 2. Unit root test results

	ADF	PP	KPSS	ADF	PP	KPSS
		Level		*first*	*difference*	
Copper	-2.053	-1.656	2.695***	-34.695***	-34.663***	0.028
Gold	-0.845	-0.830	2.803***	-19.913***	-20.851***	0.122
Nickel	-1.632	-1.462	2.782 ***	-19.574 ***	-19.436***	0.025
Tin	0.195	-1.682	1.814***	-15.172***	-38.819***	0.064
WTI	-1.331	-1.150	2.728***	-21.324***	-20.732***	0.043

*Notes: ***, ** and * indicate significance at the 1, 5 and 10 % levels, separately.*

5.2. Results from Bayesian Quantile_on_Quantile Approach

Employing the Bayesian Quantile_on_Quantile, the interaction between Gold and other assets across different quantiles could be further dug out, resulting in providing the important implication for the policy makers, especially Gold and others mineral assets in one country. Hence, we implement a series estimation and show the related results in Table 3 in this subsection.

First, from Table 3-1, we note the positive association between Gold and Nickel in the region of Nickel and Gold return quantiles above 95% and below 50%, respectively. For the corresponding quantiles of Nickel above 95% and Gold above 50%, there is a negative relationship. In addition, the regions of Gold quantiles above 95% and Nickel above 50% show also the negative relationship between these two metals.Therefore, we infer that asymmetric spillover is observed between the gold and nickel markets across different quantiles.

Table 3. Estimated Coefficients Matrix for Selected Quantiles

	Table 3-1. Gold Return Quantile					
Nickel Return Quantile		0.05	0.25	0.50	0.75	0.95
	0.05	-0.120	-0.045	0.002	0.017	0.371
	0.25	-0.050	0.021	0.026	0.029	0.177
	0.50	0.041	0.032	0.162	0.002	-0.020
	0.75	0.100	0.019	0.059	0.003	0.031
	0.95	0.493	0.008	-0.068	-0.122	-0.124

	Table3-2. Gold Return Quantile					
WTI Return Quantile		0.05	0.25	0.50	0.75	0.95
	0.05	0.013	0.003	-0.013	-0.009	0.012
	0.25	-0.061	0.040	0.008	-0.023	-0.095
	0.50	0.009	0.062	0.065	0.005	0.053
	0.75	0.241	0.172	0.061	0.105	0.046
	0.95	0.318	0.409	0.412	0.197	0.075

	Table3-3. Gold Return Quantile					
Copper Return Quantile		0.05	0.25	0.50	0.75	0.95
	0.05	0.003	0.057	0.039	0.059	-0.056
	0.25	0.099	0.060	0.000	0.115	-0.003
	0.50	0.128	0.087	0.012	0.102	0.026
	0.75	0.094	0.028	0.167	0.213	0.155
	0.95	0.438	0.042	-0.028	0.279	0.162

	Table3-4. Gold Return Quantile					
Tin Return Quantile		0.05	0.25	0.50	0.75	0.95
	0.05	0.002	0.034	0.050	0.058	-0.079
	0.25	0.112	0.072	0.021	0.069	-0.127
	0.50	0.184	0.074	-0.00	-0.004	-0.092
	0.75	0.033	0.041	-0.00	0.000	-0.161
	0.95	-0.88	-0.497	-0.40	-0.190	-0.128

Next, the interaction between Gold and WTI is estimated and displayed in Table 3-2. The coefficients for the WTI quantiles above 50% reveal positive association and those revealing the negative association with the Gold can be observed if WTI is below the 25% quantile. Besides, stronger linkages exist on the higher quantiles of the WTI, that is the magnitude of the coefficients above 95% quantile of WTI is larger compared to the others, implying that the tail-behavior of the WTI apparently exhibits connection with Gold. Hence, this evidence suggests that WTI positively affects Gold, especially when the WTI presents the bullish status.

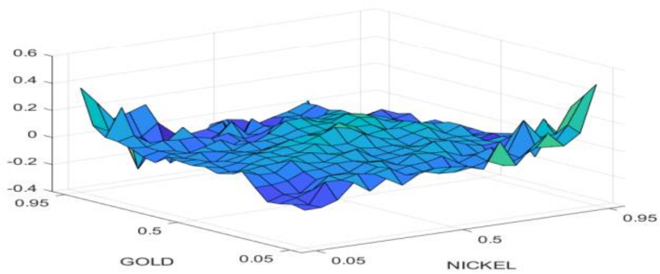
Moreover, we also examine the connection between Gold and other two different metals, Copper and Tin, and results are shown in Tables 3-3 and 3-4, respectively. Considering the results for Copper, shown in Table 3-3, in general, positive association with Gold can be found across most quantiles, where for the higher return (above 95% quantile) of Copper the coefficients are non-negative except that at the 50% quantile. Additionally, two out of five coefficients above 95% quantile Gold return are negative, especially all of below the 25% quantile Copper return. This evidence shows that positive connectedness also can be observed in the Copper.

On one hand, the results of Tin, reported in Table 3-4, reveal different pattern with preceding 3 mining assets. Specifically, the region where positive coefficients predominate is in the lower and middle return area. However, negative coefficients are almost present in the higher return region of the Tin or Gold. Notably, negative interaction with Gold can be obtained if Tin or Gold markets reveal bull markets (95% quantile). Based on the above noted findings, the association between Gold and Tin exhibits different linkages. The negatively spillover effect between them exists when either Gold or Tin is bullish market.

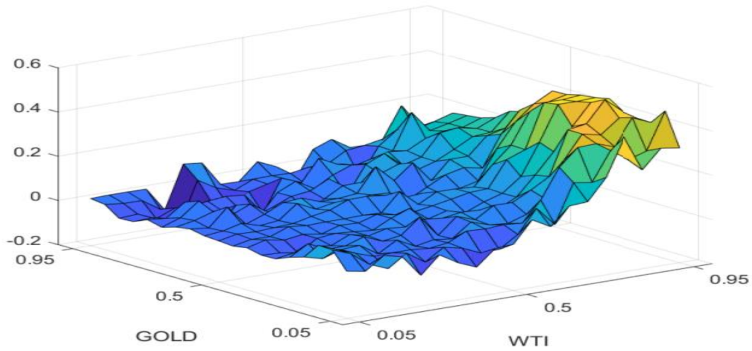
As said above, the connections among these commodities across different quantiles implicitly exist. To easily display the linkages among them, the coefficients across the varying quantile between gold and other four assets are reported on Figure 2.

Figure 2. Bayesian Quantile_on_Quantile Coefficients

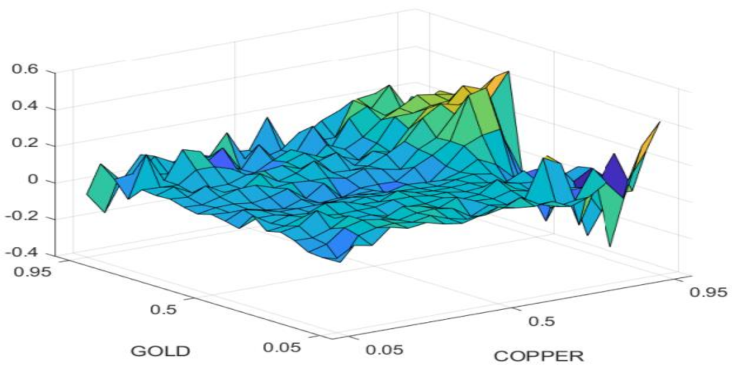
Panel (a). Impact of Nickel on GOLD Bayesian QQ model



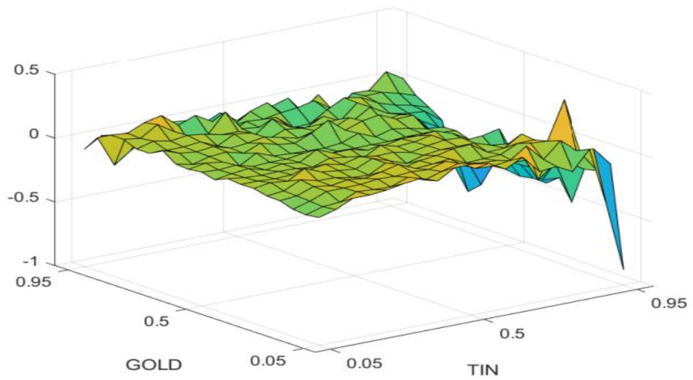
Panel (b). Impact of WTI on GO**L**D Bayesian QQ model



Panel (c). Impact of Copper on GOLD Bayesian QQ model



Panel (d). Impact of Tin on GOLD Bayesian QQ model



From the panel (a), obviously positive linkages between the Gold and Nickel are presented on the tail either Gold or Nickels at 5% quantile, while negative connection is shown at the 5% quantile for both commodities, indicating again asymmetric contagion effect. Considering the results between the Gold and WTI, shown on panel (b), the impacts of the WTI on the Gold market presents the increasing pattern where the sign of coefficients changes to the positive in higher quantiles, indicating that positive contagion effect exists when the WTI is bullish market. Viewing the panel (c), a further different pattern of linkage can be observed. Copper positive connection with Gold is majorly displayed over 50% quantile Gold, while mixture results are obtained below 50% quantile Gold, showing that the positive contagion effect presents on the tail for both commodities. Finally, focus on panel (d), negative contagion effect exhibits below 75% quantile of Gold when Tin over than 95% quantile, positive or no connection demonstrates on the remaining regions, while the extent of negative contagion effect is stronger than the positive contagion effect, implying that the Tin negatively spills over to the Gold when it is bullish.

In brief, as mentioned above, exploring the interaction across different quantiles by exploiting the Bayesian Quantile_on_Quantile regression, we find that the interaction between Gold and specific mineral assets provide different patterns. However, by examining the tail-behaviour of different assets, the positive contagion effect exists in the WTI and Copper and negative spillover effect presents in Tin, while Nickels exhibit asymmetric spillover effect.

5.3 Results from GARCH Model in Quantile_on_Quantile Form

To verify whether our approach reveals the heteroscedasticity brought about by the ARCH effect, the ARCH and GARCH tests are performed on the residual series. The results in Table 4 indicate our proposed Bayesian Quantile_on_Quantile model with strong ARCH and GARCH effects on residuals, therefore we also report the figures of the GARCH model in Quantile_on_Quantile form in Figure 3. On the left-hand side of Figure 3 we show a 3-D plots of the Quantile_on_Quantile coefficients for conditional variance (σ_t^2) and lag conditional variance (σ_{t-1}^2). These coefficients can be used to estimate half-life of a shock to the markets.

Figure 3. Bayesian heteroskedastic model (GARCH (1,1))

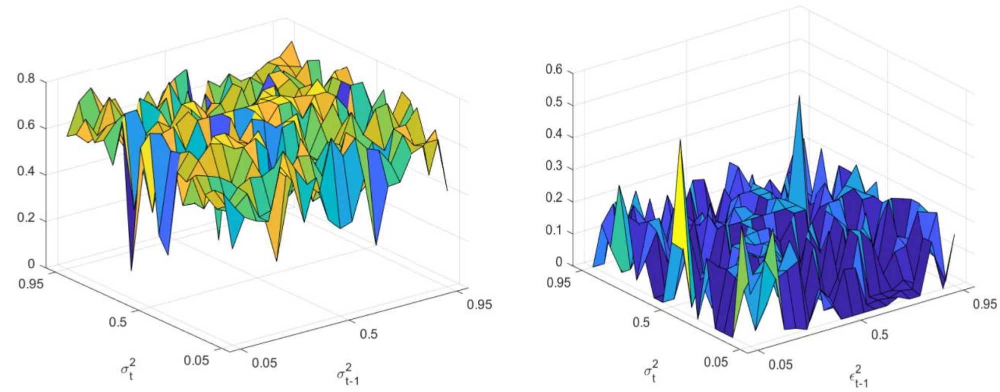


Table 4. ARCH Test and Half-Life of a Shock

Half-Life of a Shock: Max Months	*Half-Life of a Shock: Min Months*	*GARCH test*	*ARCH test*
3.072 (0.05,0.6)	0.380 (0.15,0.95)	57.127*** (0.000)	14.786*** (0.000)

Table 4 reports that the maximum and respectively minimum number of months of the half-life of a shock is about 3.072 months at the quantiles of (0.05 and 0.6) and about 0.38 months at the quantiles of (0.15 and 0.95). On the right-hand side of Figure 3, the 3-D plots of the Quantile_on_Quantile coefficients for current conditional variance $(\sigma_t^2)$and previous shock(e_{t-1}^2) are displayed. Which show previous information influences current conditional variance vary with quantiles.

5.4 Policy Implications

Based on our above empirical findings, some suggestions are proposed as follows. Standing for the policy makers such as the firms, investors, or government, the connection between Gold and Nickel, WTI, Copper, and Tin, respectively can be exploited to implement the hedging strategy. Specifically, asymmetric contagion effect of the Nickel could allow the investors buy the Nickel (Gold) when the Gold (Nickel) reveal the bearish status, resulting in reducing loss, which suffers from the inverse movement of the Gold (Nickel).

In addition, there is positive connection between Gold and WTI or Copper when latter presents strongly positive price trend. According to this evidence, the WTI and Copper could benefit the investors, especially while Gold reveal the weaker price behaviour. Finally, the positive and negative links between the Gold and Tin is obtained, where the Tin overwhelmingly show the stronger negative connection when Gold is bear status. Therefore, investors or government could apply this phenomenon to eliminate the price variation of Gold during the lower return period.

In short, policy makers could use the varying connections between Gold and other commodities to reduce the unexpected price movement of Gold, resulting in improving the return of the Gold and sustaining the performance of the firms or investors, and the exchange rate of the countries.

5. Conclusion

Examining the contagion between Gold and Oil, Copper, Nickel, Tin, this study provides an important result for investors, practitioners and policy makers. The quantile connectedness shows different patterns at different quantiles and is more sensitive to extreme positive and negative shocks than regular shocks. Our main empirical findings are outlined below.

First, the positive spillover effect is demonstrated in WTI and Copper; negative contagion effect is obtained in Tin, while Nickels show asymmetric contagion effect, suggesting that the linkages between Gold and other commodities are different.

Second, the maximum half-life of an impact is about 3.072 months at quantiles (0.05 and 0.6) and the minimum the half-life of an impact is about 0.38 months at quantiles (0.15 and 0.95). In addition, according to the results of the Quantile_on_Quantile coefficients for current conditional variance (σ_t^2) and previous information (σ_{t-1}^2), that is, the yesterday news influences current conditional variance by varying with quantiles.

To sum up, these findings could enable policy makers, including portfolio managers or the government, to decide how to exert the major policies against increasing price volatility of these commodities.

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