Time-variation between metal commodities and oil, and the impact of oil shocks: GARCH-MIDAS and DCC-MIDAS analyses

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Abstract

Extant literature establishes co-movements among commodity (metal and oil) prices; whereas oil price/shocks aggregate, as a lone predictor, has relative predictability for most financial assets. We assess the predictability of Baumeister and Hamilton's (2019) decomposed oil shocks (economic activity shocks, oil consumption demand shocks, oil inventory demand shocks, and oil supply shocks) for conditional volatilities of prominently traded precious metals (gold, palladium, platinum, and silver) using GARCH-MIDAS-X framework. The asymmetric effect of decomposed oil shocks on precious metals' volatilities is examined. The DCC-MIDAS framework allows to investigate the conditional correlations and volatility between oil and precious metal prices. Results show that precious metals exhibit hedging potentials against oil demand and supply shocks, with heterogeneity observed in the precious metal-oil shocks nexus. Asymmetry is evident in the responses of metals' volatility to oil shocks. DCC-MIDAS results reveal significant dynamic correlations between oil prices and precious metals (except for platinum). Our results are robust (sensitive) to precious metals (oil shocks) proxies. The findings are insightful for commodity market stakeholders.

Keywords: GARCH-MIDAS; DCC-MIDAS; Disaggregated oil shocks; Dynamic correlation; Platinum
JEL Classifications: G32, G12, L61

1. Introduction

Time dynamics of precious metal commodities have recently attracted the attention of investors, traders, policymakers, and producers; partly, due to the recent exponential increase in prices of these commodities, which move in tandem with the oil price. Due to continuing industrialization processes, increases in the economic uses of precious metals will continue. The flare-up in prices of gold seems to lead pricing in other precious metals that are considered as investment options and for industrial purposes in metal commodity markets (Sari, Hammoudeh, and Soytas, 2010). The increase in auto-industrial use of precious metals has also created substantial substitution options between platinum and palladium which have led to close par in prices of these two metals. Gold and silver are generally demanded for jewelry, and are traded as investment assets while silver has little industrial use and is more commodity-driven than gold (Yaya, Vo, and Olayinka, 2021; Yaya, Lukman, and Vo, 2022a).

Oil and precious metal prices are connected in some ways. Oil and precious metals are financial assets that are commonly affected by market cycles as well as market externalities. Extant literature attests to these connections, showing the diversification feats (hedge or safe haven) of the precious metals for oil commodity since they have divergent responses to market uncertainties (see Agyei-Ampomah et al., 2014; Lucey and Li, 2015; Gil-Alana et al., 2016; Qadan, 2019; Salisu et al., 2020a&b; and Salisu et al., 2021; among others). In other words, the former is perceived as an investment alternative when the oil market is in crisis; and vice versa. Shafiullah, et al. (2021) also note that oil pricing influences the composition of the international asset portfolios of oil-exporting countries as they rely solely on gold and other precious metals to manage risks in their portfolios. Since oil and precious metals are connected through exchange rates, depreciation in the US dollar will therefore reduce the value of the two commodity types.

In the production of precious metals, from the extraction process through the refining process, large amounts of hydrocarbon-rich energy (the source is majorly oil-dependent) are required to power the machinery used in precious metals production. Thus, an increase in oil price would lead to high energy pricing which would raise the cost of production of precious metals. During this period, the production of precious metals, that is, its supply will be reduced due to low demand as a result of a hike in the price of metals. On the other way, the production of precious metals benefits from a decrease in oil prices, due to lowered energy prices as a result of a reduction in the oil price. Thus, oil and precious metal pricing and production will continue to co-move due to this dependency (Sari, Hammoudeh, and Soytas, 2010). The comovement between oil and precious metals render useful information to investors to manage stocks from the two assets and carry out appropriate diversification strategy when there is turbulence.

Recently, oil price shocks have been disaggregated into four perceived causes of oil price fluctuations listed as economic activity, supply, aggregate demand, and precautionary demand shocks (see Kilian, 2009; Kilian and Park, 2009; Baumeister and Hamilton, 2019). The supply component of shocks is caused by the availability/unavailability of oil with uncertainty influencing its continuous availability. For the demand component of the shocks, fluctuations in the global financial market influence the expectations with the uncertainty on the possible shortfall in the levels of supply relative to the levels of oil demand (Hamilton, 2009; Kilian, 2008). The four disaggregated oil shocks are now being increasingly applied in the literature (Adekoya and Oliyide, 2020; Salisu and Gupta, 2021; Yaya, Ogbonna and Vo, 2022b). Thus, our interest in the perceived impacts of these four disaggregated oil shocks on prices of metal commodities and crude oil is another motivation for this paper.

There are numerous studies on the relationship between precious metals and gold which result in different and frequently debatable outcomes. We highlight a few of such empirical research examining the metal-oil price dynamic correlation in terms of shocks, co-movement, and volatility spillovers. There exist a significant long-term co-movement between the oil and gold price with a linear causality moving from the oil price to gold volatility and a nonlinear Granger causality between the two (see Zhang and Wei, 2010). Reboredo (2013) asserts that gold is not a good hedge against crude oil prices. Precious metals, specifically gold, are considered a great barricade against different financial fluctuations and oil price volatility (Lucey and Li., 2015). The dynamic connectedness between oil and metal markets can be strongly altered by the presence of shock in the oil market (Greenwood-Nimmo et al., 2015). Uddin et al. (2018) present a Markov regime-switching regression to observe the effect of the oil shocks on metals by employing Ready (2018) method of disentangling oil price dynamics into oil supply, demand, and risk. Their research shows a positive significant impact of oil supply and oil demand on metals and a negative impact due to oil risk. Husain et al. (2019) study the connectedness among stock index, crude oil, and precious metal prices in the US market by employing the time domain spillover index of Diebold and Yilmaz (2012). Their study shows that gold, silver, palladium, and platinum are net transmitters of volatility spillover, while crude oil, titanium, and steel are net receivers of volatility spillover. Following the Autoregressive Distributed Lag (ARDL) bound-testing cointegration approach in Singhal et al. (2019), the authors reveal a positive implication of gold prices on the stock market of Mexico but no significant effect on the exchange rate. Chen and Xu (2019) employ a multivariate Generalized Autoregressive Scores (GAS) model to predict the volatility and oil-gold prices relationship and find that the volatility predictability and correlation in multivariate GAS models are better than the DCC-GARCH models. Also, their methodology reflects the volatility persistence and the nonlinear interaction effect between the two commodities. The oil-gold price relationship is of great interest to market players due to its negative effects on the economy and financial markets (Tiwari et al., 2020). Khaled et al. (2020) observe an increasingly time-varying correlation between these two strategic commodities and find that oil prices transmit spillovers to gold returns and also receive spillovers from gold returns. Moreover, the continuous co-movement between oil and gold prices has renewed the interest of researchers in examining the nature of this relationship and further assessing the hedging and safe haven properties of gold against oil market risks (Yaya, Tumala and Udomboso, 2016; Gil-Alana, Yaya and Awe, 2017).

The present paper, therefore, analyzes the time-variation between oil and precious metals using mixed data sampling regression frameworks which differentiate between the short-term and long-term components of volatilities and correlations (see Engle et al., 2013). Specifically, we employ the GARCH-MIDAS-X model which decomposes the daily volatility of metal prices into short-term and long-term components whereby the long-term component is driven by monthly oil shocks. Thus, a variant of GARCH-MIDAS models that allows for the inclusion of exogenous macroeconomic variables such as oil shocks is used and the impact of oil shocks is investigated on the conditional volatility of daily metal commodity prices. Finally, the DCC-MIDAS model is employed to investigate short-term and long-term dynamic correlations existing between oil and metal commodities. This will inform portfolio managers on the possibility of oil-metal assets diversification and the strategy to adopt. To the best of our knowledge, our work is the earliest investigating the impact of monthly disaggregated oil shocks on daily metal and oil prices using MIDAS model variants in univariate and multivariate frameworks.

The rest of this paper is structured as follows: Section 2 details the MIDAS regression variants used in the paper. Section 3 presents the data and empirical results, while section 4 renders the conclusion.

2. Methodology

The GARCH-MIDAS model is the univariate MIDAS regression variant of Engle et al. (2013). It considers a return series $r_{i,t}$ of a commodity on day i in a period t which follows the process,

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\, \varepsilon_{i,t}\ ;\ \forall\ i = 1, \dots, N_t; \quad \varepsilon_{i,t}|\phi_{i-1,t} \sim N(0,1) \tag{1}$$

where N_t is the number of trading days in the period t and $\phi_{i-1,t}$ is the available information set up to day $(i-1)$ of period t. From (1), $g_{i,t}$ and T_t define the variance into a short-run component, respectively, and these changes every period t. The conditional variance is then defined as,

$$\sigma_{i,t} = T_t\, g_{i,t} \tag{2}$$

where the conditional variance dynamics of the short-run component $g_{i,t}$ follows a GARCH (1,1) process,

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu_i)^2}{T_t} + \beta g_{i-1,t} \tag{3}$$

where $\alpha > 0$ and $\beta > 0,\ \alpha + \beta < 1$ for covariance stationary conditional variance series realizations and T_t is the smoothed realized volatility in the MIDAS regression defined as,

$$log(T_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2) RV_{t-k} \tag{4}$$

where w_1 and w_2 are the weights and following Conrad et al. (2014), by restricting w_1 = 1, one is left with w_2 of which its size dictates the speed of decay of the weighing scheme function $\varphi_k(w_1, w_2)$; $RV_t = \sqrt{\sum_{i=1}^{N_t} r_{i,t}^2}$ and N = 22 to approximate the monthly realized volatility and K is the lag number on which the realized volatility (RV) is smoothed. The parameter m is the long-run constant term in the model while θ is the slope coefficient measuring the impact of the summed weighted effect of realized volatilities in the absence of any explanatory variable on the response variable (Yaya, Ogbonna and Vo, 2022b). In sum, this parameter measures the predictability of included low-frequency exogenous variables on high-frequency metal commodity price fluctuations (see Asgharian et al., 2013). The inclusion of exogenous variables along with the lagged (RV) variable facilitates the investigation of the impact of the economic variable in the long-run conditional variance series. In the case of this paper, we investigate the impact of oil. Thus, (4) is modified as,

$$log(T_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{t-k}^{Q} \tag{5}$$

where X_{t-k}^{Q} is the monthly oil shocks, and the weighting scheme used in (4) and (5) is given by a Beta lag polynomial,

$$\varphi_k(w_1, w_2) = \frac{\left(k/_K\right)^{w_1-1}\left(1-k/_K\right)^{w_2-1}}{\sum_{j=1}^{k}\left(j/_K\right)^{w_1-1}\left(1-j/_K\right)^{w_2-1}}, \quad k = 1, \dots, k \tag{6}$$

By considering the bivariate DCC model of Engle (2002), and applying it in the GARCH-MIDAS regression setup, one obtains the DCC-MIDAS model of Colacito et al. (2011) which uses the conditional covariance equation,

$$q_{o,c,t} = \bar{\rho}_{o,c,t}(1 - a - b) + a\xi_{o,t-1}\xi_{c,t-1} + b\left(q_{o,c,t-1}\right) \tag{7}$$

where $\bar{\rho}_{o,c,t} = \sum_{k=1}^{K} \varphi_k\left((w_1, w_2)\right) C_{o,c,t-1}$ and

$C_{o,c,t} = \sum_{k=t-N}^{t}\left(\xi_{o,k}\, \xi_{c,k}\right)\left(\sqrt{\sum_{k=t-N}^{t} \xi_{o,k}^{2}} \cdot \sqrt{\sum_{k=t-N}^{t} \xi_{c,k}^{2}}\right)^{-1}$ and letters o and *c* refer to log returns of oil and metal commodity prices, respectively. Thus, $\xi_{o,k}$ and $\xi_{c,k}$ are the residuals from each univariate GARCH-MIDAS model for oil and commodity price returns, respectively, and $q_{o,c,t}$ is the short-run correlation between oil and metal commodity price returns and $\bar{\rho}_{o,c,t}$ is a slowly moving long-run correlation.

The parameter space for a restricted version of the beta weighing scheme then becomes, $\Phi = \{\mu, \alpha, \beta, \theta, w_1, w_2, m\}$, in which the GARCH-MIDAS model with RV has filtered a fixed

RV for the metal commodity market return estimating the long-run variance and the impact of the RV effect driven by θ. Meanwhile, by including exogenous variables such as oil shocks as in the case of the GARCH-MIDAS-X model, where X is the exogenous variable, the parameter space is still given as above since RV is now replaced by oil shocks.

3. Data and Empirical Results

3.1 Data set

We employ four daily (high frequency) metal prices [gold, silver, palladium, and platinum], daily West Texas Intermediate (hereafter, WTI) oil prices, and four monthly (low frequency) decomposed oil shocks. The precious metal prices and the WTI oil prices were obtained from the Hotforex platform and spanned from 1 March 2014 to 31 October 2021. The monthly oil shocks are the four decomposed oil shocks of Baumeister and Hamilton (2019); spanning between March 2014 and October 2021.[1] The decomposed oil shocks include economic activity shocks (EAS), oil consumption demand shocks (OCDS), oil inventory demand shocks (OIDS), and oil supply shocks (OSS). Updated versions of these time series are found at the personal website of Professor Christiane Baumeister at https://sites.google.com/site/cjsbaumeister/research. All the price series have been transformed to returns, as a way to circumvent the problem of non-stationarity or unit roots of the series used in the main estimation.

We summarize the statistical features of the employed data in Table 1; showing the mean, standard deviation, skewness, and kurtosis, as well as the serial correlation and ARCH effect tests statistics. The average returns on all the precious metals are negatively skewed and leptokurtic, as expected of most return series. Considering the mean and the standard deviation jointly in the computation of the corresponding coefficient of variation, silver, and palladium

[1] As at March 2022 when the analysis of data for this paper commenced, disaggregated oil shocks series were updated till October 2021 on the website of Prof Christiane Baumeister, and that corresponded to 31 October 2021 in the case of daily data for metal prices.

are observed to be the most and least volatile, respectively, among the precious metals. The metal returns also exhibit evidence of higher order serial correlation and ARCH effect, which indicates that the most appropriate model for such series should be GARCH-based. Returns on the oil price are also negative on average and found to exhibit negative skewness, excess kurtosis, and evidence of serial correlation and ARCH effects. The decomposed monthly oil shocks are on average mostly negative (except for OCDS), with feats of negative skewness (except OIDS), fatter tails than the normal distribution, no higher order serial correlation, and ARCH effects (except for EAS at lag 5). The mixed frequencies of our daily (high frequency) prediction and monthly (low frequency) predictor, therefore, requires a combination of the GARCH- and MIDAS- based frameworks. Hence, our adoption of the GARCH-MIDAS model. Also, in a bid to ascertain plausible spillovers between the precious metals markets and the oil market, the DCC-MIDAS regression is employed.

Table 1: Descriptive Statistics and Pre-tests

Ticker	Mean	Standard Deviation	Skewness	Kurtosis	$Q^2(1)$	$Q^2(5)$	$ARCH(1)$	$ARCH(5)$	Frequency
Metal price returns									
Gold	0.0135	0.8675	-0.1800	6.9139	5.4232***	66.5530***	5.4216***	10.9244***	Daily
Silver	0.0058	1.6118	-0.8006	13.6672	42.4820***	214.6800***	43.2891***	30.0711***	Daily
Palladium	0.0479	1.9575	-0.8432	19.0561	26.4560***	99.1880***	26.7363***	17.4968***	Daily
Platinum	-0.0191	1.4830	-0.5820	10.8947	13.8050***	505.4700***	13.8610***	91.8745***	Daily
Oil price returns									
WTI Oil	-0.0095	2.9946	-2.6456	53.6925	45.0450***	307.3400***	45.9607***	46.7429***	Daily
Oil Shocks									
EAS	-0.1044	1.1542	-2.2294	17.7880	0.7186	27.665***	0.6786	6.3767***	Monthly
OCDS	0.0210	4.7737	-1.2141	6.6210	0.5363	4.8169	0.5066	0.7749	Monthly
OIDS	-0.2248	1.0109	0.2313	3.1976	0.4810	2.1792	0.4551	0.4302	Monthly
OSS	-0.1575	1.6774	-2.6396	18.5306	0.4924	0.9624	0.4639	0.1508	Monthly

Note: $Q^2(\#)$ and $ARCH(\#)$ denote respectively the higher order autocorrelation and the autoregressive conditional heteroscedasticity at the specified lags (#), which gives a measure of the presence of serial correlation and ARCH effects respectively. The *** denotes the statistical significance of the formal test at 1% level, where statistical significance implies the presence of the considered effect (serial correlation and ARCH).

3.2 Empirical results

The empirical results for the estimation of the metal price returns – oil shocks nexus are presented for three cases, based on the oil shocks definition: We first consider the aggregated forms of the decomposed oil shocks (EAS, OCDS, OIDS, and OSS) and report same in Table 2. We further consider the negatively and positively disaggregated forms of the decomposed oil shocks in Tables 3 and 4, respectively, as a way to ascertain whether the asymmetry effect holds with respect to the oil shock variants considered. We, therefore, present in each table, the parameter estimates of the GARCH-MIDAS model with two parameter beta weights; under four panels that are determined by the oil shocks being considered. Panels A – D corresponds to EAS, OCDS, OIDS, and OSS. The model parameters include the unconditional mean of the precious metal price returns (μ); the ARCH term (α); the GARCH term (β); the slope coefficient (θ) that indicates the stance of predictability of the monthly oil shocks for precious metals returns; the two beta polynomial weights (w_1) and (w_2); and the long run constant term (m).

From Table 2, all the parameter estimates are found to be statistically significant except for the unconditional mean of the returns on precious metals (gold, silver, and platinum). We find that the ARCH and GARCH terms are not only statistically significant at a 1% level but the sum of both terms is also found to be less than unity; an indication of a high but transient volatility persistence that may only require a longer time to fizzle out. The weights are statistically significant and greater than one; an indication that immediate past observations are assigned higher weights than far distant observations. The feat is the same across the four oil shocks (see Panels A – D of Table 2). On the estimates of the slope parameter that indicates the predictive potential of the predictor variable being considered, we find that the nexus between economic activity shocks (EAS) and the returns on precious metals (gold, silver, palladium, and platinum) are positive and statistically significant (see Panel A of Table 2). The positive response of these precious metals to economic activity shock suggests that the precious metals could act as hedges against oil market risks. We find a similitude of the stance of significantly positive metal returns – oil shocks nexus, as in the case of economic activity shocks with oil consumption demand shocks (OCDS) (see Panel B of Table 2). Summarily, the precious metals seem to have hedging potential against economic activity shocks and oil consumption demand shocks. These stances align with Salisu and Adediran (2020) that find gold as a hedge against oil shocks.

However, the metal returns – oil shocks nexuses with respect to oil inventory demand shocks (see Panel C of Table 2) and oil supply shocks (see Panel D of Table 2) are different. We find significantly negative slope coefficients, which suggest that these precious metals do not hedge against oil inventory demand and oil supply shocks. Imperatively, investors are likely to incur losses investing in such assets given uncertainties in the oil market.

Table 2: Results of GARCH-MIDAS for oil shocks (Case I)

AGGREGATE OIL SHOCKS (TWO-PARAMETER BETA WEIGHTING FUNCTION)							
	μ	α	β	θ	w_1	w_2	m
ECONOMIC ACTIVITY SHOCKS							
Gold	0.0022 [0.0023]	0.0570*** [0.0158]	0.8560*** [0.0507]	0.3030*** [0.0395]	6.3700*** [1.4200]	6.7900*** [1.5300]	0.0091*** [0.0006]
Silver	0.0008 [0.0039]	0.1090*** [0.0156]	0.7440*** [0.0417]	1.4400*** [0.1310]	5.3600*** [0.6590]	6.8800*** [1.0000]	0.0367*** [0.0022]
Palladium	0.0131** [0.0057]	0.0851*** [0.0079]	0.8570*** [0.0119]	1.7100*** [0.3150]	8.7400*** [2.6400]	12.9000*** [4.2600]	0.0612*** [0.0042]
Platinum	0.0007 [0.0042]	0.0890*** [0.0207]	0.7580*** [0.0690]	1.4600*** [0.1710]	5.8200*** [0.7170]	7.2100*** [0.9670]	0.0372*** [0.0027]
OIL CONSUMPTION DEMAND SHOCKS							
Gold	0.0018 [0.0023]	0.0654*** [0.0142]	0.8680*** [0.0368]	0.2730*** [0.0721]	1.4100*** [0.4390]	1.3100*** [0.4580]	0.0059*** [0.0006]
Silver	-0.0003 [0.0040]	0.0070*** [0.0062]	0.9000*** [0.0076]	0.6830*** [0.1530]	2.6200*** [0.7190]	8.4600** [3.4800]	0.0270*** [0.0027]
Palladium	0.0125** [0.0057]	0.0816*** [0.0076]	0.8520*** [0.0120]	1.3000*** [0.1600]	3.0900*** [0.8490]	8.1800*** [2.6400]	0.0047*** [0.0028]
Platinum	0.0005 [0.0041]	0.0971*** [0.0198]	0.7870*** [0.0512]	0.8890*** [0.1160]	2.3000*** [0.6080]	4.8200** [2.1200]	0.0255*** [0.0020]
OIL INVENTORY DEMAND SHOCKS							
Gold	0.0022 [0.0023]	0.0550*** [0.0164]	0.8580*** [0.0514]	-0.0944*** [0.0131]	5.9700*** [2.0100]	4.3300*** [1.3400]	0.0047*** [0.0003]
Silver	0.0007 [0.0038]	0.1070*** [0.0161]	0.7310*** [0.0445]	-0.4410*** [0.0426]	7.9100*** [1.6300]	5.9600*** [1.0300]	0.0152*** [0.0009]
Palladium	0.0133** [0.0056]	0.0872*** [0.0081]	0.8580*** [0.0010]	-0.7240*** [0.1190]	2.2500** [0.9040]	3.2000*** [1.1900]	0.0350*** [0.0034]

Platinum	0.0008 [0.0041]	0.0888*** [0.0205]	0.7550*** [0.0693]	0.4610*** [0.0556]	5.5700*** [1.5000]	4.4200*** [1.0000]	0.0154*** [0.0010]
			OIL SUPPLY SHOCKS				
Gold	0.0020 [0.0023]	0.0630*** [0.0151]	0.8660*** [0.0395]	-0.0870*** [0.0175]	7.1100*** [1.8900]	3.7600*** [1.1400]	0.0049*** [0.0006]
Silver	-0.0002 [0.0039]	0.0713*** [0.0068]	0.9000*** [0.0088]	-0.4460*** [0.1010]	7.9600*** [2.3300]	3.5900*** [1.1000]	0.0159*** [0.0028]
Palladium	0.0127** [0.0055]	0.2110*** [0.0200]	0.5700*** [0.0371]	-0.3690*** [0.0358]	6.4000*** [2.3300]	4.9300*** [1.8700]	0.0586*** [0.0031]
Platinum	0.0006 [0.0041]	0.0959*** [0.0193]	0.7920*** [0.0493]	-0.3210*** [0.0679]	1.0000** [0.3930]	1.4100 [1.0800]	0.0249*** [0.0034]

Note: μ is the unconditional mean of the returns on the precious metals; α is the ARCH term; β is the GARCH term; θ is the slope coefficient that indicates the stance of predictability of the monthly oil shocks for precious metals returns, and w_2 is the two beta polynomial weights; while m is the long run constant term. The figures in each cell of the table are the GARCH-MIDAS parameter estimates and their corresponding standard errors in square brackets. The ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Our findings of mixed stances of predictability, in terms of direction and/or nexus, therefore inform further consideration of the disaggregated oil shocks. While in a way, we can ascertain more clearly the hedging characteristic of the considered precious metals; we also confirm whether the asymmetry effect holds for the four decomposed oil shocks variants. In essence, does the metal market respond similarly to positive and negative oil shocks? The results in Table 3 (Case II: negative oil shocks) and Table 4 (Case III: positive oil shocks) are similarly presented under four panels, as done previously with respect to the aggregate oil shocks. From the foregoing, we find the stance of the negative oil shocks to be largely similar to that of aggregate oil shocks, with the metal markets for gold, silver, palladium, and platinum responding positively and significantly to negative decomposed EAS and OCDS. The implication here is that higher uncertainties would lead to higher returns in the precious metals (gold, silver, palladium, and platinum) markets. A recent paper by Adekoya et al. (2022) has supported this tendency of high asset price connectivity during crises such as the global financial crisis, COVID-19, and the current Russia-Ukraine war. Investors in the precious metals markets are most likely to make higher returns investing in precious metals whenever the turbulence in the oil market is occasioned by economic activities or oil consumption demand; hence, the hedging potential of the metal market against economic activity shocks and oil consumption demand shocks.

On the other hand, we find the four precious metals (gold, silver, palladium, and platinum) return to respond negatively and significantly to negative decomposed OIDS and OSS. Imperatively, the returns on investments reduce with rising uncertainty in the oil market. Investors are not likely to invest in such metal markets, as further increases in uncertainty may lead to losses. Here, the four precious metals do not offer any form of hedging option for uncertainty in the oil market that is driven by oil inventory demand and oil supply shocks. It is also noteworthy to state that the aggregate oil shocks stances are mirrored by the negative decomposed oil shocks stances, given the high degree of similarities. Also, the metals' returns – oil shocks nexuses are insensitive to the employed precious metals (gold, silver, palladium, and platinum), but sensitive to the oil shocks proxies (EAS, OCDS, OIDS, and OSS).

Table 3: Results of GARCH-MIDAS for negative oil shocks (Case II)

NEGATIVE OIL SHOCKS (TWO-PARAMETER BETA WEIGHTING FUNCTION)							
	μ	α	β	θ	w_1	w_2	m
ECONOMIC ACTIVITY SHOCKS							
Gold	0.0022 [0.0023]	0.0578*** [0.0159]	0.8540*** [0.0506]	0.2870*** [0.0376]	6.3500** [2.5300]	7.2000*** [2.6800]	0.0136*** [0.0011]
Silver	0.0010 [0.0039]	0.1100*** [0.0159]	0.7320*** [0.0429]	1.3900*** [0.1320]	6.1600*** [1.5300]	8.1600*** [1.8400]	0.0588*** [0.0042]
Palladium	0.0135** [0.0056]	0.0848*** [0.0077]	0.8620*** [0.0106]	2.7000*** [0.3500]	1.2100*** [0.2530]	2.3000*** [0.6660]	0.1150*** [0.0099]
Platinum	0.0006 [0.0042]	0.0904*** [0.0195]	0.7790*** [0.0576]	1.4500*** [0.1940]	3.7600*** [1.3800]	4.3100*** [1.4100]	0.0600*** [0.0062]
OIL CONSUMPTION DEMAND SHOCKS							
Gold	0.0020 [0.0023]	0.0625*** [0.0153]	0.8630*** [0.0419]	0.4760*** [0.0866]	2.4800*** [0.6620]	1.5500*** [0.3750]	0.0128*** [0.0013]
Silver	-0.0005 [0.0041]	0.0695*** [0.0060]	0.9070*** [0.0072]	0.9340*** [0.2850]	2.6400*** [1.0200]	6.9600 [4.4600]	0.0415*** [0.0065]
Palladium	0.0123** [0.00573]	0.0803*** [0.00775]	0.8570*** [0.01160]	1.9600*** [0.27500]	3.1200*** [0.79400]	7.8700*** [2.81000]	0.0789*** [0.00548]
Platinum	0.0007 [0.0041]	0.0991*** [0.0200]	0.7840*** [0.0505]	1.8500*** [0.2990]	1.6900*** [0.2630]	1.7200*** [0.4830]	0.0512*** [0.0048]
OIL INVENTORY DEMAND SHOCKS							
Gold	0.0022 [0.0023]	0.0596*** [0.0017]	0.8490*** [0.0506]	-0.0976*** [0.0135]	15.2000** [6.5300]	14.3000** [5.9000]	0.0016*** [0.0006]
Silver	0.0010 [0.0039]	0.1150*** [0.0160]	0.7190*** [0.0426]	-0.4930*** [0.0553]	9.8200*** [3.1800]	9.3600*** [2.8800]	-0.0009 [0.0022]
Palladium	0.0135** [0.0056]	0.0881*** [0.0081]	0.8570*** [0.0107]	-0.9120*** [0.2380]	2.4500 [1.8400]	3.3900 [2.1900]	0.0010 [0.0101]
Platinum	0.0007 [0.0042]	0.0894*** [0.0197]	0.7750*** [0.0603]	-0.5810*** [0.0882]	3.6100* [1.9200]	3.2000** [1.5700]	-0.0050 [0.0038]
OIL SUPPLY SHOCKS							
Gold	0.0020	0.0626***	0.8630***	-0.1610***	7.4600***	4.6500***	-0.0015

	[0.0023]	[0.0155]	[0.0417]	[0.0285]	[1.7900]	[1.2500]	[0.0015]
Silver	-0.0000 [0.0039]	0.0735*** [0.0070]	0.8920*** [0.0097]	-0.7670*** [0.1530]	7.8200*** [2.2100]	4.3600*** [1.2600]	-0.0137* [0.0072]
Palladium	0.0140*** [0.0053]	0.2120*** [0.0217]	0.5730*** [0.0380]	-1.0000*** [0.1030]	2.2700*** [0.8050]	2.3800*** [9.1100]	0.0208*** [0.0029]
Platinum	0.0009 [0.0041]	0.1000*** 0.0202]	0.7830*** [0.0507]	-0.6850*** [0.0942]	3.5900*** [1.3500]	2.8300*** [1.0100]	-0.0088 [0.0054]

Note: μ is the unconditional mean of the returns on the precious metals; α is the ARCH term; β is the GARCH term; θ is the slope coefficient that indicates the stance of predictability of the monthly oil shocks for precious metals returns; w_1 and w_2 are the two beta polynomial weights; while m is the long run constant term. The figures in each cell of the table are the GARCH-MIDAS parameter estimates and their corresponding standard errors in square brackets. The ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

On the nexus between precious metals (gold, silver, palladium, and platinum) returns and positively decomposed oil shocks (see Table 4), we again find a mix of significant positive (in the case of OCDS) and significant negative (in the cases of EAS, OIDS, and OSS) nexuses. The metal returns – positive (EAS, OIDS, and OSS) shocks nexus is significantly negative; which implies that decreasing uncertainty in the oil market would lead to higher returns on investments in precious metals. Only positively decomposed oil consumption demand shocks (OCDS) exhibit a positive nexus with the metal returns; thus, implying that decreasing uncertainty in the oil market would lead to a decrease in the returns on investments in the considered metal markets, while economic activity shocks (EAS), oil inventory demand shocks (OIDS) and oil supply shocks (OSS) exhibit positive nexuses with the precious metal returns (gold, silver, palladium, and platinum).

Table 4: Results of GARCH-MIDAS for positive oil shocks

POSITIVE OIL SHOCKS (TWO-PARAMETER BETA WEIGHTING FUNCTION)							
	μ	α	β	θ	w_1	w_2	m
			ECONOMIC ACTIVITY SHOCKS				
Gold	0.0023 [0.0023]	0.0691*** [0.0146]	0.8670*** [0.0350]	-2.7200*** [0.4970]	4.3000*** [0.3330]	4.3200*** [0.4560]	0.0509*** [0.0083]
Silver	0.0003 [0.0040]	0.0751*** [0.0066]	0.8980*** [0.0078]	-12.1100*** [3.0100]	4.1700*** [0.3770]	3.9600*** [0.5470]	0.2230*** [0.0505]
Palladium	0.0143** [0.0057]	0.0938*** [0.0076]	0.8600*** [0.0099]	-17.7000*** [3.7600]	4.2100*** [0.4170]	4.6400*** [0.7650]	0.3340*** [0.0614]
Platinum	0.0019 [0.0042]	0.0948*** [0.0145]	0.8580*** [0.0264]	-12.0000*** [2.8900]	4.0600*** [0.3760]	3.7900*** [0.6400]	0.2210*** [0.0488]
			OIL CONSUMPTION DEMAND SHOCKS				
Gold	0.0021 [0.0023]	0.0638*** [0.0152]	0.8590*** [0.0429]	0.4970*** [0.0799]	2.7200*** [0.6810]	6.3100*** [1.7800]	-0.0012 [0.0012]

Silver	0.0002 [0.0039]	0.0720*** [0.0066]	0.8840*** [0.0093]	2.1100*** [0.3520]	2.4200*** [0.4550]	7.0500*** [1.7000]	-0.0078 [0.0048]
Palladium	0.0127** [0.0057]	0.0865*** [0.0082]	0.8500*** [0.0122]	3.5900*** [0.5040]	1.6500*** [0.3810]	4.9300*** [1.5700]	-0.0096 [0.0084]
Platinum	0.0007 [0.0041]	0.0957*** [0.0209]	0.7670*** [0.0613]	2.4800*** [0.2830]	1.9700*** [0.4140]	4.4200*** [1.1600]	-0.0145*** [0.0038]
OIL INVENTORY DEMAND SHOCKS							
Gold	0.0023 [0.0023]	0.0669*** [0.0159]	0.8540*** [0.0430]	-0.3620*** [0.0590]	3.4100*** [0.6020]	2.2200*** [0.2910]	0.0179*** [0.0021]
Silver	0.0001 [0.0004]	0.1080*** [0.0142]	0.7600*** [0.0370]	-1.6500*** [0.2040]	3.9200*** [0.5050]	2.5600*** [0.2350]	0.0754*** [0.0074]
Palladium	0.0130** [0.0056]	0.0845*** [0.0073]	0.8580*** [0.0105]	-2.9000*** [0.3560]	1.8300*** [0.2540]	2.1600*** [0.3350]	0.1420*** [0.0127]
Platinum	0.0012 [0.0042]	0.0954*** [0.0189]	0.7920*** [0.0485]	-1.8900*** [0.2690]	2.2900*** [0.2750]	2.0600*** [0.1610]	0.0857*** [0.0099]
OIL SUPPLY SHOCKS							
Gold	0.0018 [0.0023]	0.0672*** [0.0141]	0.8670*** [0.0360]	-0.1150*** [0.0381]	1.0500** [0.4270]	1.3300 [1.0200]	0.0115*** [0.0013]
Silver	-0.00043 [0.0040]	0.0705*** [0.0068]	0.9030*** [0.0087]	-1.0600*** [0.2430]	7.0800*** [1.7200]	2.7300*** [0.6950]	0.0577*** [0.0091]
Palladium	0.0122** [0.0057]	0.0872*** [0.0084]	0.8420*** [0.0129]	-0.5120*** [0.062]	7.1500** [2.8200]	5.0000** [2.0900]	0.0748*** [0.0049]
Platinum	0.0005 [0.0041]	0.0945*** [0.0192]	0.7950*** [0.0490]	-0.6770*** [0.1100]	1.0000*** [0.2180]	1.0000*** [0.3470]	0.0514*** [0.0049]

Note: μ is the unconditional mean of the returns on the precious metals; α is the ARCH term; β is the GARCH term; θ is the slope coefficient that indicates the stance of predictability of the monthly oil shocks for precious metals returns; w_1 and w_2 are the two beta polynomial weights; while m is the long run constant term. The figures in each cell of the table are the GARCH-MIDAS parameter estimates and their corresponding standard errors in square brackets. The ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: DCC-MIDAS Estimation Results

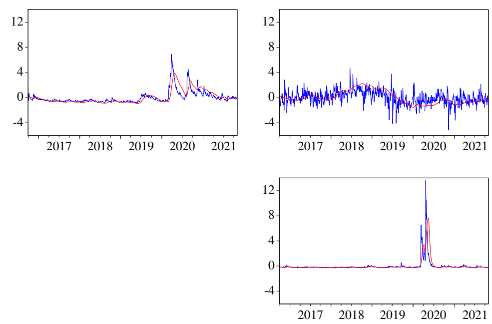
	Gold	**Palladium**	**Platinum**	**Silver**	**Oil**
GARCH-MIDAS					
μ	0.0001 [0.0002]	0.0006 [0.0004]	-0.0002 [0.0003]	-0.0004 [0.0032]	0.0009** [0.0005]
α	0.0499*** [0.0108]	0.2824*** [0.0234]	0.0867*** [0.0150]	0.0904*** [0.0105]	0.1792*** [0.0109]
β	0.8893*** [0.0493]	0.4645*** [0.0532]	0.8279*** [0.0492]	0.7493*** [0.0341]	0.6987*** [0.0466]
θ	0.0269*** [0.0067]	0.0242*** [0.0032]	0.0338*** [0.0068]	0.0331*** [0.0033]	0.0232*** [0.0062]
w_2	5.0001** [2.4169]	24.5150* [14.8940]	4.9988* [2.8527]	2.7067*** [0.6375]	33.8720* [17.9480]
m	0.0000*** [0.0000]	0.0003*** [0.0000]	0.0001*** [0.0000]	0.0071*** [0.0013]	0.0004*** [0.0001]
DCC-MIDAS (Precious metals with Oil Returns)					
a	0.0649** [0.0297]	0.0313 [0.0230]	0.0000 [0.0106]	0.0141* [0.0081]	
b	0.6309*** [0.2053]	0.7186** [0.3366]	0.1350 [13.7750]	0.9754*** [0.0176]	
w_2	1.7996** [0.8594]	7.2302** [3.0039]	3.8881** [1.7786]	1.0010 [1.3157]	

Note: μ is the unconditional mean of the returns on the precious metals; α is the ARCH term; β is the GARCH term; θ is the slope coefficient that indicates the stance of predictability of the monthly oil shocks for precious metals returns; w is the one parameter beta polynomial weights; while m is the long run constant term. The figures in each cell represent the estimates of the GARCH- and

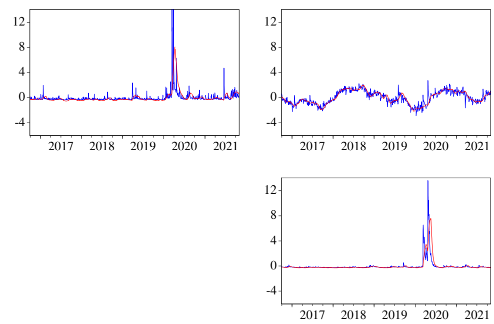
DCC-MIDAS parameters with their corresponding standard errors in square brackets. The statistical significance of these estimates at 1%, 5%, and 10% are respectively denoted by ***, **, and *.

For the DCC-MIDAS regression, to ease the computational burden in obtaining estimates of the dynamic correlation between the precious metals and oil markets, the first weight is set as, $w_1 = 1$, leaving w_2 to be computed. The results are presented under two panels: the first shows the conventional GARCH-MIDAS estimates for each precious metal and oil return. The GARCH-MIDAS section further confirms the high persistence of the series, while the DCC-MIDAS part shows some convergence for precious metals' – oil returns pairs, with significant estimates of weights at a 5% confidence level (in the cases of gold, palladium, and platinum). We only find statistically significant short-run effects $(a+b)$ in the cases of gold and silver, with the latter exhibiting a higher persistence. However, from the foregoing, and based on the convergence results as well as the observation of significantly high persistence, we conclude that the gold–oil returns pair is dynamically correlated. Intuitively, we expect volatility spillover between gold and oil markets. Conclusively, there is evidence of a dynamic correlation between the precious metals (quite evident in the cases of gold and silver) market and the oil market. Both gold and silver prices are known to move in tandem since silver is the closest substitute to gold and both assets serve similar functions. This is the reason for the long-run equilibrium relationship as a result of the cointegration between the two (Yaya et al., 2021). In that case, the transmission of shocks between them is of short-run effect.

Gold and Oil



Palladium and Oil



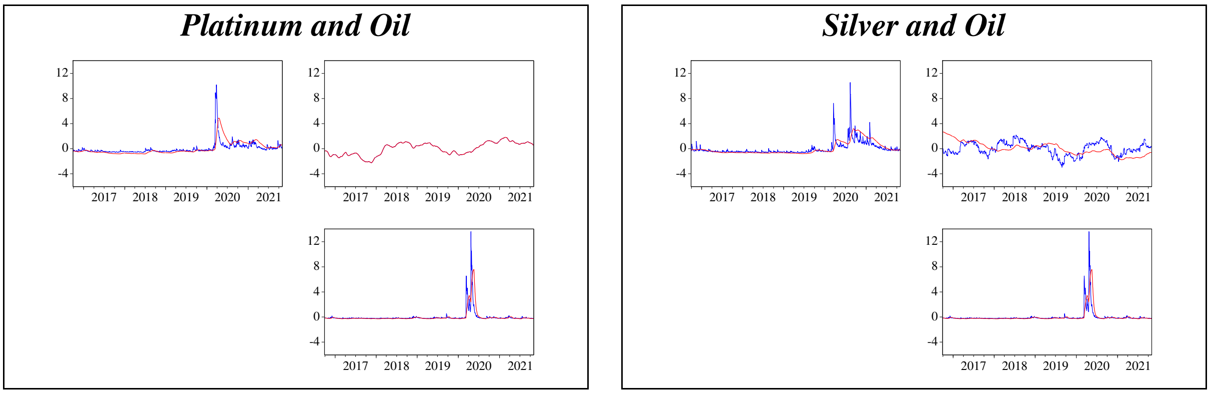


Figure 1: Dynamic Volatility and time-varying correlations

Figure 1 presents the long- and short-run volatilities[2], as well as the time-varying correlations for each precious metal and oil return. For each market pair, i.e. gold and oil, for plots on the main diagonal of each quadrant, the solid line in "red" is the long-run volatility while the dotted line in "blue" is the short-run volatility. Plots on the off-diagonal of the quadrant show the conditional correlations between the pair, i.e., long-run correlation and total correlation in solid "red" line and dotted "blue" line, respectively. We find evidence of volatility linkage across all the series and at almost the same period. During the period, gold and other precious metals experienced about a 10-year price rise marking 2019 as their strongest year since 2010. Palladium rose as high as 59% during this period in 2019 making the sharpest annual gain since 2010.[3] This period precedes the COVID-19 pandemic outbreak in 2020 where prices suddenly crashed. In Figure 1, this is observed as a period of high volatility in the early part of 2020 when the price started falling. Over the period being investigated, we observe oil to be dynamically correlated in the long run with gold (ranging between -0.03 and 0.15), palladium (ranging between -0.05 and 0.35), platinum (ranging between 0.04 and 0.31), and silver (ranging between 0.05 and 0.2). Although, the total correlations are more widely varying except in the case of the correlation between platinum and oil. However, there appears to be evidence of time-varying correlations in oil-gold, oil-

[2] The volatilities have been normalized to ensure that the values on the y-axis are the same, for easy comparison.
[3] https://www.marketwatch.com/story/gold-higher-on-track-for-strongest-year-since-2010-2019-12-31

silver, and oil-palladium with correlation in oil-platinum being insignificant; while we observe some instantaneous points of negative correlations in the cases of oil correlation with gold and palladium. Summarily, the correlations of the precious metals with oil prices vary; being mostly positive but weak. It is noted in Adekoya et al. (2022) that oil and precious metals connect more during the crisis period since crises make assets to be more integrated. Crises do trigger supply shocks which would lead to a rise in oil prices, and since this is coming from oil, the global commodity and financial markets will be affected. However, a fall in the price of oil is often caused by a demand shock, thus, this could reduce the linkages between oil and precious metal prices.

4. Conclusion

We investigate the effect of time-variation of the precious metals' – oil price returns and shocks nexuses using the univariate GARCH-MIDAS-X regression, and the bivariate DCC-MIDAS model. The former allows for the decomposition of the daily (higher frequency) volatility of metal prices into short-term and long-term components, with the accommodation of a long-term component that is driven by monthly (lower frequency) oil shocks. The latter allows for investigating both short-term and long-term dynamic correlations between oil and metal commodities' price returns. Daily gold, silver, palladium, and platinum; and daily WTI oil prices, spanning 1 March 2014 to 31 October 2021 are analyzed; with the monthly decomposed oil shocks (economic activity shocks, oil consumption demand shocks, oil inventory demand shocks, and oil supply shocks), applied under the GARCH-MIDAS framework.

Findings in the paper indicate homogeneity in the cases of economic activity shocks, oil consumption demand shocks, and oil supply shocks; with tendencies for metals' price volatility to increase as economic activity shocks or oil consumption demand shocks increase, while there is a tendency for metal price volatility to reduce with oil supply shocks. Heterogeneity is only found in the case of oil inventory demand shocks where gold, silver, and palladium metal price volatility are likely to reduce, and platinum metal price volatility is likely to increase. This heterogeneity implies that different production costs are involved in the extraction and final production of precious metals as oil production and consumption profiles affect these. Also, precious metals are meant for different personal and industrial purposes. It also informs us about the hedging potential of metal commodities against oil shocks. Based on asymmetry, the results infer the possibility of precious metals having hedging potential against economic activity shocks and oil consumption demand shocks, while returns on investments are likely to be unfavourable when investors are faced with oil inventory demand shocks and oil supply shocks. Findings based on DCC-MIDAS regression indicate that gold-WTI, palladium-WTI, and silver-WTI relationships are significantly time-varyingly correlated, while that of platinum-WTI is not significant. Thus, diversification advantage can be explored by portfolio managers in the case of significantly correlated assets.

The results in this paper will therefore be of interest to portfolio managers trading oil and precious metals to know on one hand, how types of oil shocks impact the two assets, and on the other hand, realize the spillovers or correlations between oil and metal assets as such relationship informs portfolio diversification. It informs them that global assets connect more during crisis periods (global financial crisis, COVID-19, and Russia-Ukraine war) and caution should be taken in adopting a hedging strategy that would maximize profits and reduce risks.

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