The Role of Global Economic Conditions in Forecasting Gold Market Volatility: Evidence from a GARCH-MIDAS Approach

Afees A. Salisu*, Rangan Gupta** and Elie Bouri***

Abstract

In this study, we examine the role of global economic conditions in forecasting gold market volatility using alternative measures. Based on the available data frequency for the relevant series, we adopt the GARCH-MIDAS approach which allows for mixed data frequencies. We find that global economic conditions contribute significantly to gold market volatility albeit with mixed outcomes. While the results lend support to the safe-haven properties of the gold market, the outcome is influenced by the choice of measure of global economic conditions. For completeness, we extend the analyses to other precious metals such as silver, platinum, palladium, and rhodium and find that global economic conditions forecast the volatility of gold returns better than other precious metals. Our results are robust to multiple forecast horizons and offer useful insights into plausible investment choices in the precious metals market.

Keywords: Precious Metals Volatility, Global Economic Conditions, Mixed-Frequency

JEL Codes: C32, C53, E32, Q02

* Corresponding author. Department for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam; Faculty of Business Administration, Ton Duc Thang University, Ho Chi Minh City, Vietnam. Email: afees.adebare.salisu@tdtu.edu.vn.

** Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.

*** USEK Business School, Holy Spirit University of Kaslik, Jounieh, Lebanon. Email: eliebouri@usek.edu.lb.

1. Introduction

The role of gold as a traditional "safe haven" is well-recognized (see for example, Baur and Lucey, 2010; Baur and McDermott, 2010, 2016), which implies that investors are often attracted to this precious metal due to its ability to offer portfolio diversification and/or hedging benefits during periods of economic slowdown, turmoil in traditional financial markets, increased geopolitical risk or economic uncertainty, and the high degree of risk aversion associated with low investor sentiments (Tiwari et al., 2020; Bonato et al., forthcoming a). Understandably, an accurate forecast of gold return volatility is of paramount interest to investors and portfolio managers in their asset pricing models (such as, gold derivatives pricing) as well as in hedging strategies to mitigate portfolio risks. Not surprisingly, there exists a large amount of literature on empirical finance that aims to forecast gold volatility based on various metrics that capture the uncertain environment of the financial markets and macroeconomy (see for example, Pierdzioch et al. (2016), Fang et al., (2018), Asai et al. (2019, forthcoming), Bouri and Jalkh (2019), Demirer et al. (2019), Gkillas et al. (2019), Bonato et al., (forthcoming b), and the references cited therein).

Against this backdrop, the objective of our current study is to forecast daily gold returns volatility based on a new measure of global economic conditions recently developed by Baumeister et al. (2020) to forecast energy markets. This newly developed measure covers conditions of real economic activity, commodity prices (excluding precious metals), financial indicators, transportation, uncertainty, expectations, weather, and energy-related measures, and hence, encapsulates the various measures capturing the position of risk in the overall world economy, as discussed above, for forecasting gold market volatility. Given that the index measure of global economic conditions is available at monthly frequency, and given that we want to forecast gold market volatility on a daily basis (to avoid the loss of information that would result from averaging the daily volatility to a lower monthly frequency (Clements and Galvão, 2008; Das et al., 2019), we rely on the generalized autoregressive conditional heteroskedasticity (GARCH) variant of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model. Note that the decision to forecast gold market volatility at the daily frequency is not only due to the underlying statistical reason of providing more accurate measures of volatility, but because high frequency forecasts are indeed more important for investors in terms of making timely portfolio decisions. In addition, with gold market volatility also capturing global economic uncertainty, which affects the slow-moving real economy (Piffer and Podstawski, 2018), accurate forecasts of the same, would help policymakers forecast the future path of low-frequency domestic real activity variables using methods of nowcasting (Banbura, 2011), and thus come up with appropriate and early policy responses to prevent a possible recession. Even though the main focus is on forecasting gold volatility using the global economic conditions index, we also forecast the volatility of four other precious metals, silver, platinum, palladium, and rhodium, using this index. In addition, we forecast the volatility of the returns of all five metals (gold, silver, platinum, palladium, and rhodium) using five alternative, but narrower, measures of global economic activity (primarily associated with output), that have been used in the literature, for the sake of comparison. To the best of our knowledge, this is the first attempt to forecast daily volatility of precious metals using a broad index of global economic conditions based on a GARH-MIDAS approach.

The remainder of the paper is organized as follows: Section 2 outlines the econometric framework, while Section 3 discusses the data. Section 4 presents the empirical results from the in-sample and out-sample forecasting analyses, and Section 5 concludes.

2. Methodology

We briefly describe the GARCH-MIDAS framework that is adopted as the model for forecasting the metal price volatility based on the economic activity index. The chosen framework is based on the frequency differences of the metal returns (daily) and the economic activity (monthly), respectively. The MIDAS framework combines variables sampled at different frequencies within a single framework to model volatility (GARCH), hence the name – GARCH-MIDAS. It is most appropriate for this study as it provides an avenue that minimizes information loss due to aggregation or splicing, as the case may require. Therefore, using both daily (metal price volatility - the predicted series) and monthly (economic activity - the predictor series) data, in a bid to garner all plausible information in the estimation process, the GARCH-MIDAS model is applied[1].

[1] Salisu and Ogbonna (2019) discuss some computational advantages of the MIDAS regressions, while Engle et al. (2013) provide technical details of the multiplicatively decomposed conditional variance into high- and low-frequency components of the MIDAS model.

The metal (gold, silver, platinum, palladium, and rhodium) price volatilities are generated as the conditional variance of returns on metal prices. The return on metal prices is defined as $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ is the precious metal price on day i month t; with $t = 1,\ldots,T$ and $i = 1,...,N_t$ denoting the monthly and daily frequencies and N_t indicating the number of days in any given month t. The model for the daily precious metal returns, comprising the constant conditional mean and the conditional variance is defined as:

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \qquad \forall \; i = 1,...,N_t \tag{1}$$

with

$$\varepsilon_{i,t} \left| \Phi_{i-1,t} \sim N\left(0,1\right)\right. \tag{2}$$

where $\Phi_{i-1,t}$ indicates the available information set at day $i-1$ of period t. The second item on the right-hand side of equation [1], the conditional variance part, is decomposed into two parts: the short-run component $h_{i,t}$ that is of a higher frequency and assumed to follow the conventional GARCH(1,1) process, and the long-term volatility captured by τ_i in a rolling window framework. By definition, the conditional variance is:

$$h_{i,t} = \left(1-\alpha-\beta\right) + \alpha \frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_i} + \beta \overline{h}_{i-1,t} \tag{3}$$

where μ is the unconditional mean of the stock return, α and β are the ARCH and GARCH terms, respectively, such that $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The originally monthly varying long-term component is re-structured to vary daily, given that the days across periods t are rolled back without keeping track of it. This is given by:

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k \left(\omega_1, \omega_2\right) X_{i-k}^{(rw)} \tag{4}$$

where X_{i-k} is the predictor variable, the "rw" superscript denotes the implementation of the rolling window framework and $\phi_k(\omega_1, \omega_2)$ is the weighting scheme, such that $\phi_k(\omega_1, \omega_2) \geq 0, \quad k = 1, \ldots, K$ and sums to one, for the parameters of the model to be identified. The one-parameter beta polynomial weighting scheme is applied based on its flexibility and popularity (see Colacito, Engle and Ghysels, 2011):

$$\phi_k(\omega_1, \omega_2) = \frac{\left[k/(K+1)\right]^{\omega_1 - 1} \times \left[1 - k/(K+1)\right]^{\omega_2 - 1}}{\sum_{j=1}^{K} \left[j/(K+1)\right]^{\omega_1 - 1} \times \left[1 - j/(K+1)\right]^{\omega_2 - 1}} \qquad [5]$$

3. Data Description and Preliminary Analysis

The dataset used in this study comprises five (5) metals' (gold, silver, platinum, palladium, and rhodium) daily returns and six (6) monthly economic activity proxies (global economic conditions indicator (GECON), real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP)). The metal price data in US dollars is derived from Datastream. Three of the economic activity datasets (GECON, OECDIP, and KINDX) are obtained from the research segment of the respective websites of Professor Christiane Baumeister[2] and Professor James D. Hamilton[3], and the remaining three (RCPF, GSPF, and RSCF) are directly provided to us by Professor Baumeister, for different time intervals, occasioned by data availability. In other words, the return series have different start dates but the same end date, while the economic activity datasets have different start and end dates (see the date intervals in Table 1). Consequently, the precious metals with the highest (13,566) and lowest (7,257) daily points correspond to gold and rhodium, respectively, while those of the economic activities are 622 for OECDIP and 547 for RCPF, GSPF and RSCF. We consider the nexus between gold returns and all six economic activities for our main estimation, while the remaining metals' returns are considered as a form of robustness.

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[2] https://sites.google.com/site/cjsbaumeister/research.
[3] https://econweb.ucsd.edu/~jhamilton/.

At this stage, it is important to discuss the six indices used in our analysis as the drivers of precious metal market volatility. Kilian's (2009) measure of real economic activity is based on single-voyage dry-cargo freight rates, with the idea behind the index being that changes in real shipping costs expressed in deviations from a linear time trend capture the cyclical component of demand for industrial commodities. Given that shipping of raw industrial materials is linked to future production of manufacturing goods, Kilian (2009) treats this index as a proxy for the state of the global business cycle. Hamilton (2019) argues that removing a deterministic linear time trend is a poor way to isolate the cyclical component in real shipping costs and is not supported by the data, and hence, we use the month-on-month growth rate of this index. As an alternative to Kilian's (2009) index, Baumeister et al. (2020) propose the real shipping cost factor, which is based on the common factor derived from the unbalanced panel of disaggregated data consisting of a cross-section of 61 freight rates for individual shipping routes for a set of industrial commodities such as coal, iron ore, and fertilizer. The index of world industrial production is developed by Baumeister and Hamilton (2019), and this measure remains closer to the traditional concept of economic activity as measured by the physical volume of output generated in the industrial sector. Baumeister and Hamilton (2019) construct an updated version of a monthly index of industrial production covering OECD countries and six major emerging markets (Brazil, China, India, Indonesia, the Russian Federation and South Africa) by applying the same methodology used by the OECD. The real commodity price factor extracts a global factor related to business cycle fluctuations from monthly growth rates of real prices of 23 basic industrial and agricultural commodities used as inputs in the production of final goods, and hence excludes precious metals, as suggested by Alquist et al. (2019). Following Ravazzolo and Vespignani (forthcoming), who suggest that steel is an important input for many industries including construction, transportation, and manufacturing, and that it is a relatively homogenous commodity that is traded freely worldwide, the global steel production factor is derived from monthly world steel production by accounting for the problem of structural breaks due to aggregation caused by changes in the number of reporting countries. The reader is referred to Table 2 of Baumeister et al. (2020) for further details regarding these alternative indices.

As seen from the discussion above, the literature focuses on developing indicators that capture cyclical variation in global real economic activity. These measures are rather limited in scope since they are all constructed based on a single category of variables such as shipping freight rates, commodity prices, steel production or industrial production. But it must be realized that global economic conditions as they relate to precious metal markets are likely to be captured better by a basket of variables that include new categories to cover additional dimensions of the global economy, rather than a narrow set of variables. Given this, we now have the global economic conditions index of Baumeister et al. (2020), which is a factor, derived using the expectation-maximization (EM) algorithm, based on 16 indicators associated with economic activity, commodity prices, financial indicators, transportation, uncertainty and expectation measures, weather and energy-related indicators. The reader is referred to Table 7 of Baumeister et al. (2020) for further details regarding the wide array of variables included in the construction of the index.

Table 1: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	CV	Frequency	N	Start Date	End Date
Returns									
GOLD	2.82E-04	0.012	0.131	30.638	4.37E+03	Daily	13566	02/04/1968	24/04/2020
SILVER	1.62E-04	0.021	-0.104	20.821	1.32E+04	Daily	13045	27/04/1970	24/04/2020
PLATINUM	1.43E-04	0.016	-0.481	13.017	1.12E+04	Daily	11560	05/07/1976	24/04/2020
PALLADIUM	3.26E-04	0.020	-0.271	11.283	6.01E+03	Daily	8689	06/01/1987	24/04/2020
RHODIUM	1.57E-04	0.019	0.327	43.538	1.18E+04	Daily	7257	02/07/1982	24/04/2020
Economic Activity									
GECON	2.04E-03	0.457	-1.409	7.304	2.24E+04	Monthly	566	1973M02	2020M03
RCPF	4.12E-17	0.459	-0.389	7.589	1.11E+18	Monthly	547	1973M02	2018M08
GSPF	-2.51E-03	0.655	0.222	4.201	-2.62E+04	Monthly	547	1973M02	2018M08
RSCF	5.91E-03	0.757	-0.494	6.577	1.28E+04	Monthly	547	1973M02	2018M08
KINDX	-8.83E-02	14.499	-0.631	9.834	-1.64E+04	Monthly	618	1968M04	2019M09
OECDIP	2.23E-01	0.647	-1.610	12.670	2.90E+02	Monthly	622	1968M05	2020M01

Note: real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).

The summary statistics of the data series are given in Table 1. The mean values of the return series range between 1.43E-04 and 3.26E-04, corresponding to platinum and palladium, respectively. However, gold and silver returns are the least and most volatile, respectively, among the precious metals investigated, as suggested by the standard deviation. Also, confirmed by the coefficient of variation, the same two metals' returns are the least and most widely varying. Gold and rhodium returns are positively skewed while the remaining precious metals are negatively skewed. All the returns are leptokurtic as expected of returns series. Economic activities on the other hand are found to have a mix of positive (GECON, RCPF, RSCF, and OECDIP) and negative (GSPF, and KINDX) averages, while KINDEX is the most volatile economic activity proxy. For the period under consideration, RCPF appears to be more widely varied than any other economic activity proxy. While all the economic activity proxies are leptokurtic, we find all, except GSPF, to be negatively skewed.

In the preliminary analysis, we test for conditional heteroscedasticity using a formal volatility test – the autoregressive conditional heteroscedasticity (ARCH) test, and serial correlation using Q-statistics and Q^2-statistics for autocorrelation and higher order correlation, respectively. These tests are conducted for all variables at lags 5, 10 and 20, and the results are presented in Table 2. All the variables (both metal returns and economic activity proxies) exhibit ARCH effects. This is expected as it is often found to be a characteristic feature of high frequency data. Consequently, the significant ARCH effect suggests the appropriateness of a GARCH based model framework. There is also evidence of serial correlation in all the metals' returns (except platinum at lag 5) and all the economic activity proxies (except RCPF at the three specified lags). However, higher order autocorrelation is statistically significant for all the variables. Given the above-mentioned characteristics and the frequency mix of the metals' returns and economic activity proxies, we adopt a framework that incorporates the mixed data sampling technique into a GARCH framework – GARCH-MIDAS.

Table 2: Preliminary Analysis

	$ARCH\,(5)$	$ARCH\,(10)$	$ARCH\,(20)$	$Q\,(5)$	$Q\,(10)$	$Q\,(20)$	$Q^2\,(5)$	$Q^2\,(10)$	$Q^2\,(20)$
				Returns					
GOLD	141.80***	78.11***	50.09***	12.29**	22.18**	65.066***	779.28***	1065.80***	1687.00***
SILVER	514.68***	290.20***	150.45***	16.80***	27.51***	44.13***	4198.10***	6487.90***	8371.20***
PLATINUM	249.56***	159.92***	83.98***	9.05	21.002**	42.505***	1927.40***	3519.80***	5008.10***
PALLADIUM	141.09***	85.50***	46.57***	17.85***	18.89***	39.53***	1042.40***	1669.30***	2161.90***
RHODIUM	207.48***	130.08***	74.14***	27.00***	101.60***	149.53***	1516.50***	2451.30***	3004.50***
				Economic Activity					
GECON	2.42**	1.88**	1.96***	32.83***	41.77***	68.12***	12.793**	16.976*	38.228***
RCPF	8.05***	4.26***	2.25***	4.46	5.36	10.85	46.44***	66.25***	78.35***
GSPF	29.98***	16.13***	9.07***	40.65***	78.64***	296.92***	118.99***	143.03***	152.77***
RSCF	13.48***	9.13***	5.03***	12.471**	26.76***	46.55***	83.88***	142.38***	177.59***
KINDX	18.56***	11.16***	6.02***	10.779*	23.31***	41.94***	126.10***	178.20***	244.74***
OECDIP	11.68***	6.14***	3.07***	74.53***	84.71***	110.50***	25.18***	26.20***	27.26

Note: real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).

4. Results and Discussion

As previously stated, the GARCH-MIDAS model framework is adopted for this study. We proceed to ascertain the predictability of precious metals' returns based on the economic activity index. We consider gold returns and all six economic activity proxies for the main estimation (Tables 3 and 4), while the returns on silver, platinum, palladium, and rhodium are considered for robustness (Table 5 and Appendix Table A1). We use the full data sample of gold returns to estimate the parameters of the GARCH-MIDAS model in a bid to establish predictability and thereafter, split the data sample into two equal halves for robustness of predictability and forecast evaluation. Thus, the out-of-sample forecast performance of the various measures of global economic conditions is evaluated. In essence, we first present the impact of each of the economic activity proxies on gold return volatility and thereafter we determine the measure that best forecasts the volatility of gold returns based on the root mean square error (RMSE).

4.1. Predictive power of Economic Activities for Gold Volatility

The estimates of the parameters of the GARCH-MIDAS model are presented in Table 3. They include the unconditional mean for gold returns (μ); the ARCH and GARCH terms (α and β, respectively) in the short term component; the sum of weighted rolling window exogenous variable (θ), indicating the predictability of the monthly economic activity on the daily gold return volatility; adjusted beta polynomial weight (w); and the long run constant term (m). We find, across the economic activity proxies, statistically significant α and β, with the latter indicating high degrees of volatility persistence, and the sum of both being less than one indicating a mean reverting property. This result indicates that shocks to gold returns are unlikely to be permanent, though they may linger for a longer time period before fizzling out. This stance is the same across the economic activity proxies considered. We also find statistical significance and non-significance in the cases of μ and m, respectively, across the economic activity proxies. The estimated beta weight is significant in all except RSCF and KINDX.

Table 3: Predictive power of Economic Activities for Gold Volatility

	μ	α	β	θ	w	m
			Full Data Sample			
GECON	3.91E-05	0.0257***	0.9743***	-2.7940***	31.4160***	3.75E-03***
	[7.71E-05]	[0.0005]	[0.0005]	[0.3673]	[4.6814]	[4.22E-04]
RCPF	4.69E-05	0.0255***	0.9744***	-0.9436***	49.9020***	3.01E-03***
	[7.71E-05]	[0.0006]	[0.0006]	[0.1774]	[12.0750]	[3.47E-04]
GSPF	3.67E-05	0.0264***	0.9736***	3.1091*	1.8529**	3.31E-03***
	[7.70E-05]	[0.0006]	[0.0006]	[1.7011]	[0.8182]	[4.45E-04]
RSCF	3.42E-05	0.0257***	0.9742***	-0.3713*	14.5330	3.18E-03***
	[7.72E-05]	[0.0006]	[0.0006]	[0.1922]	[9.0571]	[3.40E-04]
KINDX	6.83E-05	0.0188***	0.9801***	0.0005	5.2780	1.39E-04***
	[7.73E-05]	[0.0002]	[0.0002]	[0.0004]	[4.1189]	[9.41E-06]
OECDIP	6.36E-05	0.0191***	0.9800***	0.0833***	2.5348***	1.19E-04***
	[7.62E-05]	[0.0002]	[0.0002]	[0.0099]	[0.1810]	[8.29E-06]
			50% Data Sample			
GECON	3.30E-05	0.0190***	0.9810***	-1.1613***	23.4380***	1.42E-03***
	[1.17E-04]	[0.0006]	[0.0006]	[0.1690]	[3.6630]	[1.79E-04]
RCPF	3.18E-05	0.0197***	0.9802***	0.7789**	4.3491**	1.08E-03***
	[1.17E-04]	[0.0007]	[0.0007]	[0.3588]	[1.7258]	[1.57E-04]
GSPF	2.86E-05	0.0205***	0.9794***	1.8363**	2.3549***	1.19E-03***
	[1.18E-04]	[0.0008]	[0.0008]	[0.7736]	[0.7402]	[2.02E-04]
RSCF	2.53E-05	0.0185***	0.9814***	-0.1418**	16.1680	1.08E-03***
	[1.18E-04]	[0.0007]	[0.0007]	[0.0712]	[10.0900]	[1.32E-04]
KINDX	1.94E-04	0.0500***	0.9000***	0.0984***	5.0000***	5.65E-04***
	[3.45E-04]	[0.0043]	[0.0092]	[0.0048]	[0.0235]	[2.77E-05]
OECDIP	2.12E-05	0.0224***	0.9776***	3.2662***	1.9449***	1.08E-03***
	[1.16E-04]	[0.0009]	[0.0009]	[1.1140]	[0.3310]	[2.35E-04]

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).

The slope parameter (θ) in the MIDAS filter specification, which gives an indication of the predictability stance of the corresponding economic activity employed, is negative (GECON, RCPF, and RSCF) and positive (GSPF, KINDX, and OECDIP), and statistically significant in all except KINDX employed on the full data sample. A significant coefficient indicating the predictive power of KINDX, as well as other economic activity proxies, for gold price volatility is however observed when 50% of the data sample is used, with negative predictive values in the case of GECON and RSCF. These results indicate that the predictability results may be sensitive to the chosen data sample. Lower economic activities (GECON, RCPF, and RSCF) and (GECON, and RSCF) are found to increase gold return volatility when the full and 50% data samples, respectively, are used. Consequently, the positive or negative nexus between gold return volatility and economic activity is dependent on the choice of economic activity employed, as well as the choice of data. Nonetheless, the outcome seems to suggest that not all the various measures used for global activity truly measure it properly. It is expected that as global activity improves, trading in gold should fall as it is a safe-haven (see Baur and McDermott, 2016), so volatility should fall which is what is consistently seen for the two data samples using the global activity measures GECON and RSCF. Put differently, if gold is considered a safe-haven, lower economic activity would increase trading in the metal and hence volatility should rise. However, some other economic activity indices such as GSPF, KINDX, and OECDIP which consistently turn up positive relationships with gold returns appear to see the metal from the perspective of any other financial asset where any improvement in global economic activity is seen as a reflection of improved financial market trading activities, among other things, which ultimately give rise to higher volatility.

Our results are generally comparable to those of Fang et al. (2018), who argue that economic policy uncertainty improves the forecast of gold variance, but provide a nice addition through their reliance on a large set of global economic activities (Baumeister et al., 2020) and a focus on various precious metals (see Section 4.3). They also add to the growing literature that uses only one variable (e.g., silver volatility, as in Bouri and Jalkh (2019), or risk aversion, as in Demirer et al. (2019)) while predicting the volatility of gold.

4.2. Out-of-Sample Forecast Evaluation

We proceed to examine the forecast error of the GARCH-MIDAS model relating gold price volatility to various economic activities. Here, the root mean square error (RMSE) is used, with values closer to zero indicating higher precision and better performance, when confronted with two or more contending models. This would form the basis for determining the most precise economic activity in the prediction of gold price volatility. We perform the out-of-sample forecast evaluation using 50% of the data sample, based on three forecast horizons: 60-, 120- and 180-days ahead out-of-sample forecast horizons (see Table 4).

In the out-of-sample forecast evaluation, the least RMSE is recorded when the GECON measure is incorporated as the exogenous variable in the GARCH-MIDAS model framework and, this proxy is the most preferred for gold return predictability using the 50% data sample regardless of the forecast horizon. This further attests to the preference for GECON in the in-sample predictability results where the proxy shows gold as a safe-haven. Consequently, forecasting with this attribute of the gold market improves the forecast performance of the GARCH-MIDAS framework in producing accurate estimates for gold market volatility. As with the predictability results reported in Table 3, next to the GECON measure, in terms of the out-of-sample forecast performance, is the RCPF measure which also supports the safe-haven property of the gold market. Given the need to understand future events through the information available in data, the GECON measure, closely followed by the RCPF measure, presents the most suitable forecast regardless of the specified forecast horizon. Therefore, it is not out of place to conclude that any predictive model that accounts for the safe-haven property of the gold market produces better forecast results.

Table 4: RMSE Results (50% of full Sample)

Economic Activity	Out-of-Sample		
	$h=60$	$h=120$	$h=180$
GECON	**1.657E-05**	**1.497E-05**	**1.695E-05**
RCPF	1.775E-05	1.551E-05	1.725E-05
GSPF	1.831E-05	1.605E-05	1.758E-05
RSCF	1.775E-05	1.582E-05	1.745E-05
KINDX	1.256E-04	9.058E-05	1.535E-04
OECDIP	1.798E-05	1.581E-05	1.741E-05

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).

4.3. Additional Analysis

By way of extension, we replicate all the analyses for the other precious metals - silver, platinum, palladium, and rhodium. Two objectives are of interest here. First, like the gold market, we attempt to examine the role of the various measures of global economic conditions in predicting the return volatility of other precious metals. Second, we compare the forecast results of these measures with those obtained for the gold market. The RMSE results are presented in Table 5 for the 60-, 120- and 180-days out-of-sample periods. The predictability results are presented in the appendix and, like the gold market, the results are mixed.

For the out-of-sample forecast evaluation (Table 5), the RCPF measure of global economic conditions is found to consistently outperform the other global economic activity proxies across the three out-of-sample forecast periods in the case of silver and platinum, having the least RMSE values in comparison with others. For palladium, while the RCPF measure is still preferred in the 60-days out-of-sample period, the GSPF measure outperforms the others when higher out-of-sample periods (120- and 180-days) are considered. Other measures such as the KINDX and RSCF equally perform well in the 180-days out-of-sample forecast period. For rhodium, the RCPF measure performs best in the 60- and 120-days out-of-sample forecasts, while the RSCF and KINDX measures are both found to have the least RMSE values for the 180-days out-of-sample period. Overall, the results show that, while the performance of the global economic indices is mixed across the precious metals considered, it appears that RCPF, in addition to predicting the volatility of these precious metals, does so preferably better than any other economic activity proxy considered in this study. In other words, on average, the RCPF measure may be a suitable predictor of the analysis of the role of global economic conditions in the predictability of the return volatility of the selected precious metals (other than gold). This is somewhat similar to the outcome of the forecast analyses for the gold market where the RCPF measure closely follows the GECON which is the preferred proxy for global economic conditions for this market. This outcome further strengthens our argument that the choice of the proxy for global economic conditions has a role to play in the predictability of return volatility of precious metals.

Table 5: RMSE Results (Robustness Check)

Economic Activity	Out-of-Sample			Out-of-Sample		
	$h=60$	$h=120$	$h=180$	$h=60$	$h=120$	$h=180$
		Silver			**Platinum**	
GECON	5.904E-04	2.971E-03	**2.483E-03**	1.877E-04	3.129E-04	2.873E-04
RCPF	**5.903E-04**	**2.969E-03**	**2.483E-03**	**1.876E-04**	**3.124E-04**	**2.868E-04**
GSPF	5.922E-04	2.974E-03	2.491E-03	**1.876E-04**	3.128E-04	2.871E-04
RSCF	5.904E-04	2.971E-03	2.487E-03	1.881E-04	3.131E-04	2.876E-04
KINDX	5.905E-04	2.971E-03	2.487E-03	1.966E-04	3.151E-04	2.981E-04
OECDIP	5.906E-04	2.970E-03	2.485E-03	1.878E-04	3.146E-04	2.883E-04
		Palladium			**Rhodium**	
GECON	8.802E-04	1.823E-03	1.589E-03	2.899E-04	1.398E-03	1.182E-03
RCPF	**8.782E-04**	1.821E-03	1.589E-03	**2.894E-04**	**1.397E-03**	1.182E-03
GSPF	8.791E-04	**1.818E-03**	**1.585E-03**	1.338E-03	1.869E-03	1.792E-03
RSCF	8.786E-04	1.819E-03	**1.585E-03**	2.899E-04	1.399E-03	**1.180E-03**
KINDX	8.791E-04	1.819E-03	**1.585E-03**	2.899E-04	1.399E-03	**1.180E-03**
OECDIP	8.879E-04	1.831E-03	1.594E-03	2.897E-04	1.399E-03	1.183E-03

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).

Comparatively, and judging by the RMSE values, the global economic conditions forecast the return volatility of the gold market better than other precious metal markets regardless of the choice of measure of global economic conditions. Since the GECON measure, which produces the best forecast for gold, supports its safe-haven property, we are more inclined to conclude that any forecasting model that accounts for this feature will produce better forecast results than those that do not.

5. Conclusions

The role of gold as a traditional safe-haven is well-established in academia as well as in the financial media, which implies that investors use this precious metal for portfolio diversification and/or hedging during periods of economic slowdown, turmoil in traditional financial markets, increased geopolitical risk and economic uncertainty, and the high degree of risk aversion associated with low investor sentiments. Given this, we try to forecast gold returns volatility based on a new measure of global economic conditions which encapsulates the various dimensions of the abovementioned risks. We apply the GARCH-MIDAS model to forecast daily gold volatility based on a monthly index of global economic conditions. Notably, we compare the gold market results with volatility forecasts of silver, platinum, palladium, and rhodium, and consider alternative narrower measures of global economic activity in forecasting the volatility of these precious metals.

We find that gold volatility responds to global economic conditions albeit with mixed outcomes. Importantly, the measures of global economic conditions that support the safe-haven property of gold produce better forecast results than other measures of global economic activity that oppose the safe-haven property. Further results involving other precious metals also produce mixed outcomes but, comparatively, the global economic conditions seem to forecast the volatility of gold better than the volatility of other precious metals.

Our results have important implications for both investors and policymakers. In particular, using the information content of the broad measure of economic conditions around the world, investors could accurately forecast gold returns volatility, and that of other precious metals, which, in turn, would help them design optimal portfolios to mitigate the risks associated with other financial assets. Given that gold market volatility captures economic uncertainty, accurate forecasting would provide information about the future path of the economy contingent on the evolution of uncertainty, which can then be fed into mixed-frequency models to produce forecasts of wide ranges of low-frequency metrics of domestic economic activity, and thus design appropriate policy responses to prevent the possibility of economic downturns.

As part of future research, it would be interesting to use the new measure of global economic conditions to forecast crude oil volatility, with the analysis justified by the fact that crude oil is the highest traded commodity in the world market.

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APPENDIX

Table A1: Predictive power of Economic Activities for the volatility of other Metals

Metal	Economic Activity	μ	α	β	θ	w	m
Silver	GECON	-1.65E-04	0.1023***	0.8893***	-0.0923	23.6860	5.87E-04***
		[2.08E-04]	[0.0040]	[0.0041]	[0.0932]	[54.7140]	[1.20E-04]
	RCPF	-1.65E-04	0.1029***	0.8886***	0.2831*	8.8961	5.80E-04***
		[2.08E-04]	[0.0041]	[0.0041]	[0.1721]	[7.8691]	[1.15E-04]
	GSPF	-1.81E-04	0.1013***	0.8900***	0.1807***	38.1000**	5.58E-04***
		[2.08E-04]	[0.0040]	[0.0041]	[0.0666]	[17.5520]	[1.09E-04]
	RSCF	-1.65E-04	0.1031***	0.8880***	0.4411*	2.8722	5.67E-04***
		[2.07E-04]	[0.0041]	[0.0042]	[0.2541]	[1.9128]	[1.11E-04]
	KINDX	-6.16E-05	0.1025***	0.8903***	-0.0040	15.4170	6.61E-04***
		[2.09E-04]	[0.0040]	[0.0040]	[0.0090]	[42.1810]	[1.59E-04]
	OECDIP	-6.35E-05	0.1024***	0.8904***	-0.0674	9.7807	6.74E-04***
		[2.07E-04]	[0.0040]	[0.0040]	[0.1622]	[32.8120]	[1.69E-04]
Platinum	GECON	-2.36E-04	0.0453***	0.9529***	-0.2658***	49.3430***	4.57E-04***
		[1.72E-04]	[0.0018]	[0.0018]	[0.0796]	[14.8150]	[1.10E-04]
	RCPF	-2.45E-04	0.0453***	0.9532***	-0.1598***	48.1310**	4.54E-04***
		[1.68E-04]	[0.0018]	[0.0018]	[0.0561]	[22.8560]	[1.16E-04]
	GSPF	-2.52E-04	0.0473***	0.9510***	0.0340	43.9790	4.56E-04***
		[1.69E-04]	[0.0019]	[0.0019]	[0.0387]	[64.9920]	[1.20E-04]
	RSCF	-2.50E-04	0.0487***	0.9492***	0.2086	2.8529	4.34E-04***
		[1.70E-04]	[0.0019]	[0.0019]	[0.2823]	[4.2178]	[1.14E-04]
	KINDX	-2.72E-04*	0.0706***	0.9209***	0.0518***	5.1207***	2.99E-04***
		[1.63E-04]	[0.0028]	[0.0029]	[0.0063]	[0.0444]	[3.63E-05]
	OECDIP	-2.44E-04	0.0452***	0.9532***	0.2555**	7.5021*	3.53E-04***
		[1.69E-04]	[0.0018]	[0.0018]	[0.1151]	[3.8708]	[9.83E-05]
Palladium	GECON	1.02E-04	0.1438***	0.8159***	-0.8685***	10.3010***	4.32E-04***
		[2.35E-04]	[0.0074]	[0.0079]	[0.0896]	[1.5962]	[3.55E-05]
	RCPF	1.31E-04	0.1261***	0.8401***	0.1002	10.1500	3.79E-04***
		[2.23E-04]	[0.0064]	[0.0074]	[0.0763]	[16.5110]	[3.25E-05]
	GSPF	1.01E-04	0.1289***	0.8354***	1.5067***	2.0247***	3.95E-04***
		[2.39E-04]	[0.0065]	[0.0074]	[0.3117]	[0.3749]	[3.17E-05]
	RSCF	1.61E-04	0.1335***	0.8363***	-1.9017***	1.3608***	3.69E-04***
		[2.12E-04]	[0.0070]	[0.0076]	[0.2786]	[0.1060]	[3.50E-05]
	KINDX	1.21E-04	0.1273***	0.8385***	0.0077***	49.4890*	3.76E-04***
		[2.23E-04]	[0.0065]	[0.0074]	[0.0028]	[28.1400]	[3.07E-05]
	OECDIP	1.22E-04	0.1291***	0.8265***	-0.3902***	17.2330***	4.48E-04***
		[2.42E-04]	[0.0070]	[0.0087]	[0.0452]	[4.4830]	[3.10E-05]
Rhodium	GECON	-7.10E-06	0.2187***	0.7721***	0.8139***	3.1949***	7.30E-04***
		[1.67E-04]	[0.0056]	[0.0036]	[0.3019]	[0.4335]	[2.63E-04]
	RCPF	4.09E-05	0.2248***	0.7634***	2.5251***	1.2683***	7.45E-04***
		[1.69E-04]	[0.0062]	[0.0037]	[0.8279]	[0.0830]	[2.45E-04]
	GSPF	4.63E-05	0.0500***	0.9000***	0.1000***	5.0000***	2.28E-03***
		[1.42E-03]	[0.0060]	[0.0122]	[0.0048]	[0.4804]	[1.42E-06]
	RSCF	2.40E-05	0.2242***	0.7702***	-1.6548***	18.5100***	1.53E-03***
		[1.28E-04]	[0.0034]	[0.0035]	[0.1109]	[0.4050]	[1.01E-04]
	KINDX	2.32E-05	0.2224***	0.7701***	-0.0468***	13.5610***	8.59E-04***
		[1.22E-04]	[0.0026]	[0.0027]	[0.0022]	[0.3848]	[3.90E-05]
	OECDIP	-2.89E-05	0.2235***	0.7671***	2.4933***	1.4927***	8.53E-05**
		[1.65E-04]	[0.0058]	[0.0037]	[0.9204]	[0.0662]	[4.25E-05]

Note: Real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP).