Climate risk and Gold

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Highlights

- Climate risk predictability for gold return volatility is evaluated.
- Climate risk is partitioned into transition and physical risks.
- Transition risk is positively related with gold return volatility.
- Physical risk is negatively related with gold return volatility.
- Higher out-of-sample forecast & economic gains are realized with climate risk.

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Abstract

In this paper, we examine the predictive content of both transition and physical risks for the volatility of gold return as well as the utility gains of observing these risks. Our results offer the following distinct contributions to the literature. One, we show that the return volatility of gold has a positively significant relationship with transition risk and a negatively significant relationship with physical risk. Given some salient features of gold, its safe-haven property, and its rarity in nature, our result appears very plausible. Two, we find evidence for out-of-sample predictability between the return volatility of gold and both transition and physical risks although with greater predictive prowess from the former. Lastly, we confirm that accounting for both transition and physical risks guarantees higher economic gains for a utility-maximizing investor that observes these risks in the gold market. We further demonstrate the robustness of our findings to multiple forecast horizons and alternative commodities.

Keywords: Climate change-related risk; Gold; Transition risk; Physical risk; Forecast; Utility metrics

1. Introduction

In this study, we examine the nexus between climate change and the return volatility of the gold price. The nexus is not far-fetched given the fact the mining of gold has become increasingly more challenging as most "easy gold" has already been mined and therefore miners have to overcome immensely difficult challenges before assessing quality gold which oftentimes has severe environmental impact. These challenges have led to additional cost of mining gold and culminated in higher prices. Additionally, the environmental impact of gold mining heightens global discussion about the safety of the process, carbon emission resulting from burning fossil fuels and its implication for climate change. For instance, the combustion of carbon during the mining of metals (gold inclusive) results in the production of carbon (IV) oxide – CO_2 - and other greenhouse gases (GHGs) that accumulate in the atmosphere. These typically add up to unfavorable climate change (risk), including greater global temperatures, increased climatic variability, and possibly rising sea levels (Pindyck, 2013). Putting the foregoing in perspective, the majority of silver is generated as a byproduct of the production of gold, copper, lead and zinc, with only one third coming from dedicated silver mines. Silver production causes significant mercury emissions into the air, soil, and water, and when it is extracted by small-scale miners, a lot of mercury is utilized, which causes significant harm to human health and the environment[4]. Similarly, owing to the high global demand for high-tech products, the annual manufacture of PCs, cell phones, tablet computers and other electronic and electrical devices for examples, uses some ten of billion dollars' worth of gold and silver which utilize 320 tons and 7,500 tons, respectively. However, when these products reach the end of their usable life and become electronic waste (e-waste), less than 15% of these precious metal "deposits" are recovered for reuse. The rest is discarded, creating potential health and environmental hazards[5].

Thus, pricing of associated cost of these mining activities could affect the price behaviour of these metals (see Tost et al., 2020; Ulrich et al., 2022). Although, the large demand for gold and silver are usually from non-industrial end (Hillier, draper and Faff, 2006), the process leading to their extraction equally makes them a suitable class of metals worthy of studying from climate change perspective[6]. Put differently, when the actions aimed at mitigating the impact of climate change are intensified, the activities in the relevant commodity markets are expected to respond to these dynamics, hence, volatility in their prices. This position aligns with that of Bernett (2019) who opines that climate policies that aim to restrict oil exploration would cause oil firms to fast-track extraction which will lead to a decrease in oil price, and by extension, translate into higher oil price volatility (Gupta and Pierdzioch, 2021).

Notwithstanding the role precious metals play in terms of their contributions to emissions, there is no study to the best of our knowledge that simultaneously examines the connection between climate risk and precious metals from both academic and investments perspectives. The only related study is that of Gupta and Pierdzioch (2022), however, this work is limited to forecast analyses as it does not assess the potential economic gains of observing climate risks. Extending this study to include the analysis of utility gains offers more insightful outcomes and compelling motivation for observing climate risk in the relevant commodity market. In addition, we employ a different methodology (see Westerlund and Narayan, 2012, 2015) that accommodates the salient features of the climate risk data used in the empirical analyses. As demonstrated in the next section, we observe the presence of persistence and conditional heteroscedasticity effects in the predictor

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[4] Silver – a toxic threat to our health and environment. Retrieved from http://www.env-health.org/IMG/pdf/silver_fact_sheet.pdf

[5] https://unu.edu/news/news/only-15-of-gold-and-silver-used-in-high-tech-goods-is-recovered.html

[6] For example, for every ounce of gold produced in 2019, gold miners released on average, 0.8 tonnes of CO_2 equivalent (https://www.spglobal.com/marketintelligence/en/news-insights/blog/greenhouse-gas-and-gold-mines-nearly-1-ton-of-co2-emitted-per-ounce-of-gold-produced-in-2019).

series which have to be dealt with in the estimation process. Accounting for these salient features when they exist tends to improve forecast outcomes (Westerlund and Narayan, 2012, 2015)[7]. This consideration of a different methodology relative to Gupta and Pierdzioch (2022) in a way provides more robust results as to the role of methodology in the climate-resource nexus.

More explicitly, we estimate both the in-sample and out-of-sample predictability of climate risk for predictability of gold return volatility. We utilize the recent daily frequency climate risk index developed by Faccini, Matin and Skiadopoulos (2021, 2022) which comprises physical risk (which deals with the losses suffered due to climate change) and transition risk (which covers the response to mitigate and adapt to the paradigm shift in environmental sustainability). With this distinction, we are able to evaluate investors' sentiment in the gold market to the variants of climate risk. It may be interesting to know if the market is more sensitive to physical risk than transition risk and vice versa.

Our interest in volatility rather than prices is stressed by the notion that higher market risks pose greater threats to future investments and which further explains why investors are usually hesitant to make investments during turbulent times. Therefore information on market risks (where market volatility serves as a useful proxy) that may be exacerbated by climate change risk is essential for making investment decisions (see also Salisu et al., 2022). While the focus of this study is on the predictability of climate change risk for gold return volatility, we equally assess the same for the volatility of silver price returns for robustness purposes.

To begin with, we note that an increase in climate risk has no definitive effect on the economy, until the component of climate risk being considered is factored in. For instance, an increase in any of the physical risk factors (global warming - GW & natural disaster - ND) and international summit, a component of transitional risk, would impact the economy negatively. Implying that an increase in the news coverage of the physical risk factors (GW and ND) will create a societal concern which can impact investor sentiments and consequently the entire economy. Likewise, an increase in international summit factor which basically indicates the level of global discussion around tax on pollutants is always "bad news" for investors and the economy

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[7] Several empirical studies have demonstrated the usefulness of this methodology in improving forecast outcomes when some salient features are present in the predictor series such as persistence and conditional heteroscedasticity effects (see for example, Narayan and Bannigidadmath, 2015; Narayan and Gupta, 2015; Phan et al., 2015; Bannigidadmath and Narayan 2016; Devpura et al., 2018; Salisu et al. 2019a, 2019b, 2019c, 2019d, 2021; among others)

as it implies an additional cost of production (Faccini et al., 2021). Meanwhile, when there is an increase in climate policy coverage, it may signal a decrease or increase in transitional risk depending on the political party making the policy. In the US for instance, members of the Democratic Party are notable for supporting climate change while members of the GOP are often tagged denialists and as such this impacts the way both parties approach climate change.

The foregoing has a broad theoretical footing in the environmental Kuznets curve (EKC) hypothesis which relates environmental quality to economic finesse. The link between several measures of environmental ruin such as CO_2 emission from mining activities and call to transition to net zero emission is believed to follow the EKC hypothesis. Increased emissions which degrade the ecosystem would result from excessive fossil fuel combustion during the early stages of mining. However, according to EKC, once environmental damage reaches a certain threshold, societies and the governments start to pay more attention to it and use a variety of policies to improve the condition of the environment. Thus, there is an inverse U-shaped relationship between mining activity and carbon emission and/or climate change (see also, Stern, 2018). Specifically, the theoretical relationship between precious metals and climate change also relates to whether precious metals are a safe haven for risk associated with climate change. It is equally related to using intensively some precious metals in producing renewable energy necessary for mitigating reliance on fossil fuel (Grandell et al., 2016). For instance, some metals such as silver and platinum play a critical role in producing renewable energy (Dutta, 2019). Silver is heavily utilized in the photovoltaic process for producing solar energy. Also, it is well known that palladium has been widely used in catalytic converters to reduce harmful gases in automobile exhaust (Erdoğan et al., 2022). Thus, it is safe to conclude that the volatility in the price of these precious metals are directly related to green finance and by extension, climate change.

From our empirical results, we show that the information content of climate risk can be exploited to improve the return volatility of gold as well as that of silver. The outcome of this analysis is mixed, first, we observe that while transition risk may have a negative impact on gold return volatility, physical risk positively impacts the market. In the case of transition risk, both of its components, US climate policy and international summit, have positive and significant effect on volatility of gold return. Thus, an increase in the news coverage of transition risk appears to heighten gold market risk. Second, the negative impact of physical risk suggests that global warming and natural disaster (which constitute its components) may have cost implication among other things on gold prices. Incidence of wildfire, flood or earthquake in mining areas puts mining activities on hold and adds to the cost involved in setting up mining equipment or replacing new ones. Our results hold for both in- and out-of-sample analyses. Further economic analyses suggest that the model that incorporates climate-risk yields higher economic gains compared to the benchmark model which ignore it. Following this introduction, the remainder of this study is structured as follows. We present the data and summary statistics in Section 2. In Section 3, our adopted methodology is documented, while in Section 4, we discuss the results. Finally, we conclude the paper in Section 5.

2. Data and Preliminary Analysis

Our dataset consists of the variants of climate risk as computed by Faccini, Matin and Skiadopoulos (2021) using textual analysis of climate-change news over the period of 2000-2018. The authors classified climate risks into two broad groups, transition and physical risks. Topics on the United State climate policy (US_CP) and international summits (IS) are captured in the former while the former consists of news on global warming (GW) and natural disaster (ND). On the methodology employed in constructing the index, the authors followed the Latent Dirichlet Allocation (LDA) (see also, Blei et al. (2003), Hansen et al. (2018)) which uses an unsupervised textual analysis method to construct the climate risk factors. The Thomson Reuters news archive, a leading media on financial news, serves as the basis for the search of keywords and the search is limited to four relevant topics with clear interpretation and relevance to the financial market namely; the occurrence of natural disasters, the role of emissions in relation to global warming, U.S. climate policy (actions and debate), and international climate-change summits.[8] In addition, we obtain daily gold price data from www.investing.com and thereafter we compute a 20-day annualized return volatility of gold prices. Our data scope is limited to the available data for the climate risk (see Faccini et al, 2021, 2022). However, for the sake of robustness, we replicate the analysis for the return volatility of silver prices.

We provide some relevant (descriptive and formal) statistics in Table 1 to describe the data and also justify the choice of methodology adopted in this study. Looking at the mean and deviation values in Table 1, it could be inferred here that discussion around global climate change,

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[8] We are grateful to Faccini, Matin and Skiadopoulos (2021) for sharing the data with us.

especially with respect to formulating policies to mitigate its effect and how to punish climate offenders in terms of tax increment has been on the rise. We make similar deductions for natural disasters, although the spate of its occurrence is not as high as other components of climate risk, however the level of the recorded volatility is very alarming judging by both standard deviation and coefficient of variation. The components of natural disasters such as flooding, wildfires, earthquake, drought and other forms of environmental hazards may be responsible for the high deviation/variation. Unsurprisingly, global warming records a modest mean value and has the least volatility among the various components of climate risk. The effect of global warming is hardly felt directly except when manifested in the occurrence of natural disaster therefore global discussions around it is always subsumed in discussions about natural disasters. In further describing our data, as shown in Table 1, we find the return volatility of gold to have a close mean and standard deviation value which implies that gold may have been very volatile in the past 2 decades. While probing further, we investigate the presence of model biasing and mis-specification features such as persistence, higher order serial correlation and ARCH effect. Our result validates the presence of all the features implying that during model specification, the model of choice must be one that accounts for all these salient features.

In Figures 1 and 2, we illustrate the co-movement between return volatility of both gold and silver with each of the components of transitional and physical risks. We observe somewhat co-movements between return volatility of gold and US climate policy depicting a form of positive relationship between both variables. However, in the case of internal summit and the two other physical risk components (global warming and natural disaster), they appear to trend negatively with return volatility of gold. These observations are further subjected to empirical scrutiny in the in-sample predictability as well as out-of-sample forecasts as demonstrated in the subsequent sections.

Table 1: Summary Statistics and Preliminary Analysis

	Transition risks		Physical risks			
	Climate Policy	Int'l Summit	Global Warming	Natural Disasters	Gold RV	Silver RV
			Summary Statistics			
Mean	0.7288	0.4870	0.3861	0.2751	15.7877	26.1166
Standard Deviation	1.0359	0.8121	0.6087	7.2305	13.3061	13.1368
Coefficient of Variation	142.1378	166.7556	157.6535	2628.3170	84.2814	50.3006
			Conditional Heteroscedasticity Effects			
$ARCH(10)$	20.6290***	8.9173***	30.4166***	23.0560***	2.9876***	1.9001**
$ARCH(20)$	15.8433***	10.0818***	19.6865***	14.6283***	59.8699***	64.1728***
$ARCH(30)$	11.4710***	8.4576***	13.7263***	10.7217***	38.5778***	42.8615***
			Serial Correlation and Persistence tests			
$Q(10)$	749.23***	654.69***	719.31***	537.19***	47.858***	1175.6***
$Q(20)$	1281.6***	1170.2***	1058.7***	1094.4***	1117.3***	1162.1***
$Q(30)$	1820.6***	1748.5***	1315.9***	1082.2***	1135.2***	69.243***
$Q^2(10)$	344.52***	120.64***	445.72***	26.798***	3.2190	1048.9**
$Q^2(20)$	682.69***	317.64***	616.77***	964.61***	992.66***	1041.3***
$Q^2(30)$	878.06***	480.64***	718.67***	966.31***	997.42***	19.397***
Persistence	0.4210***	0.4041***	0.3480***	0.9758***	0.9871***	0.9840***

Note: The ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Gold_RV, and Silver_RV denote the return volatilities of Gold and Silver respectively, computed each from their return series.

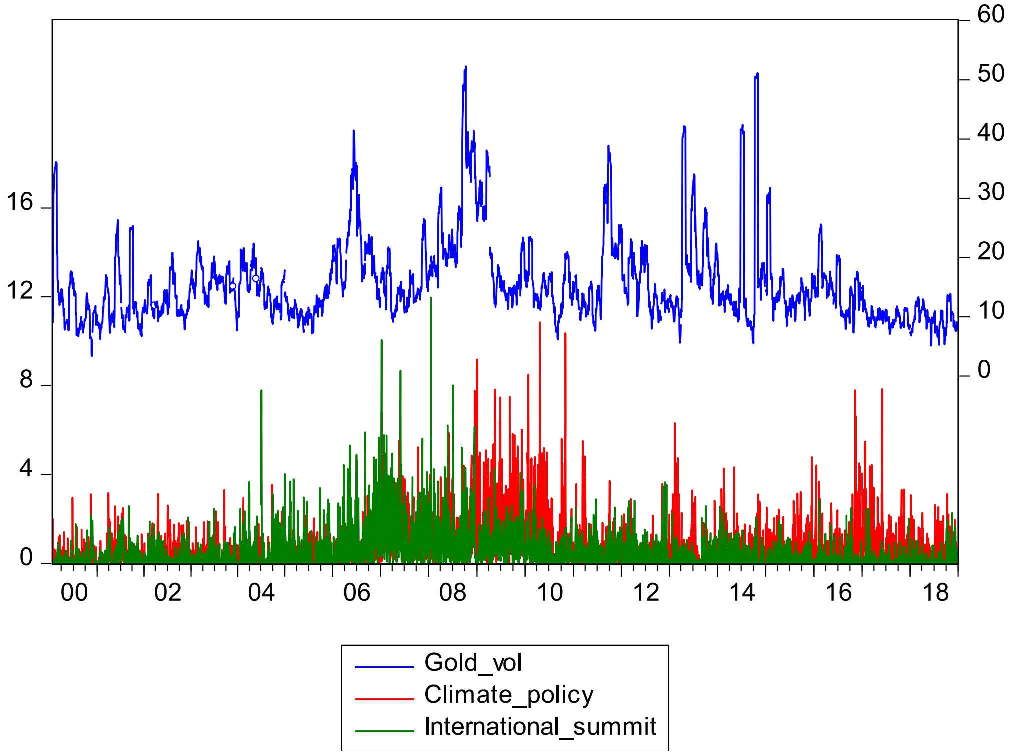

Fig. 1: Gold Realized Volatility and Transition Climate Risk

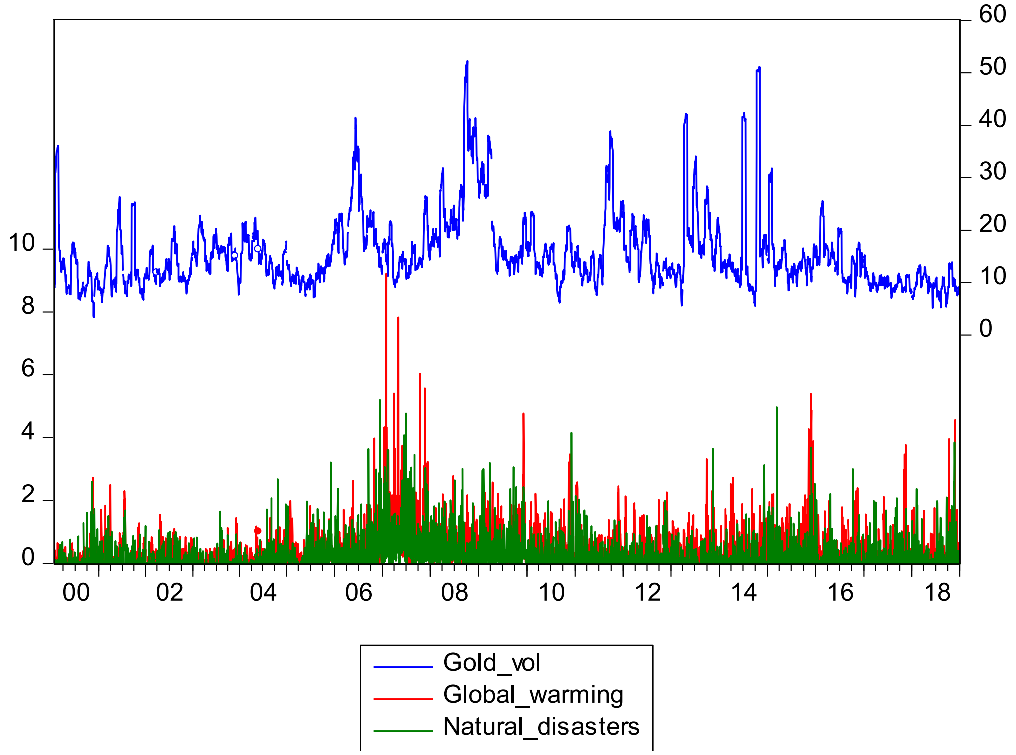

Fig. 2: Gold Realized Volatility and Physical Climate Risk

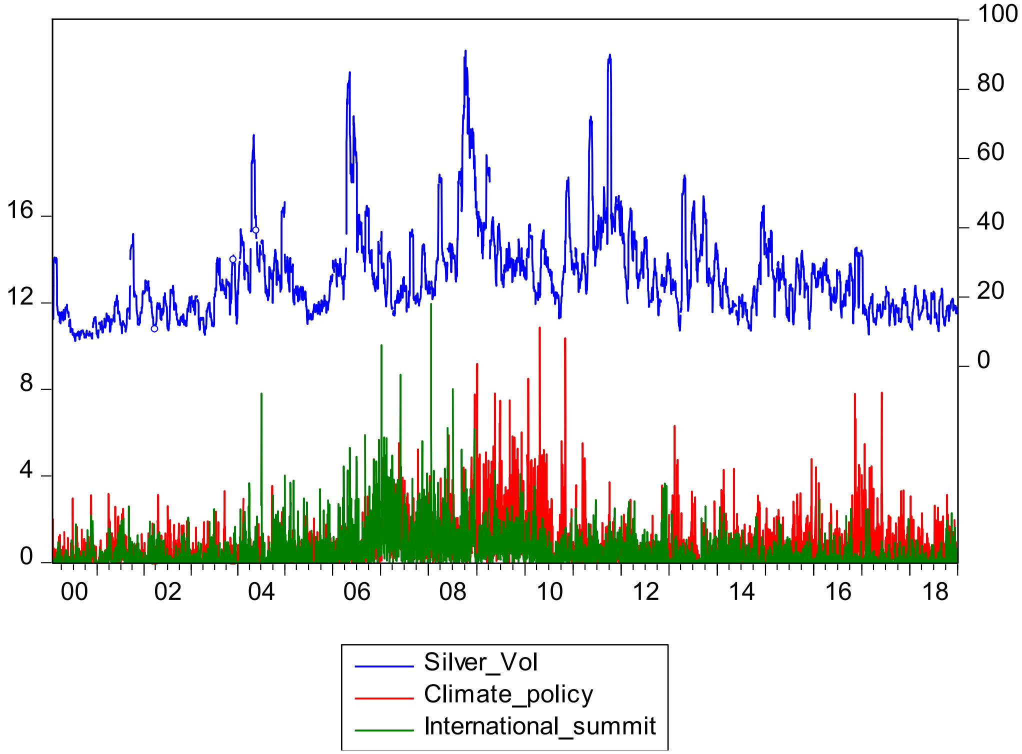

Fig. 3: Silver Realized Volatility and Transition Climate Risk

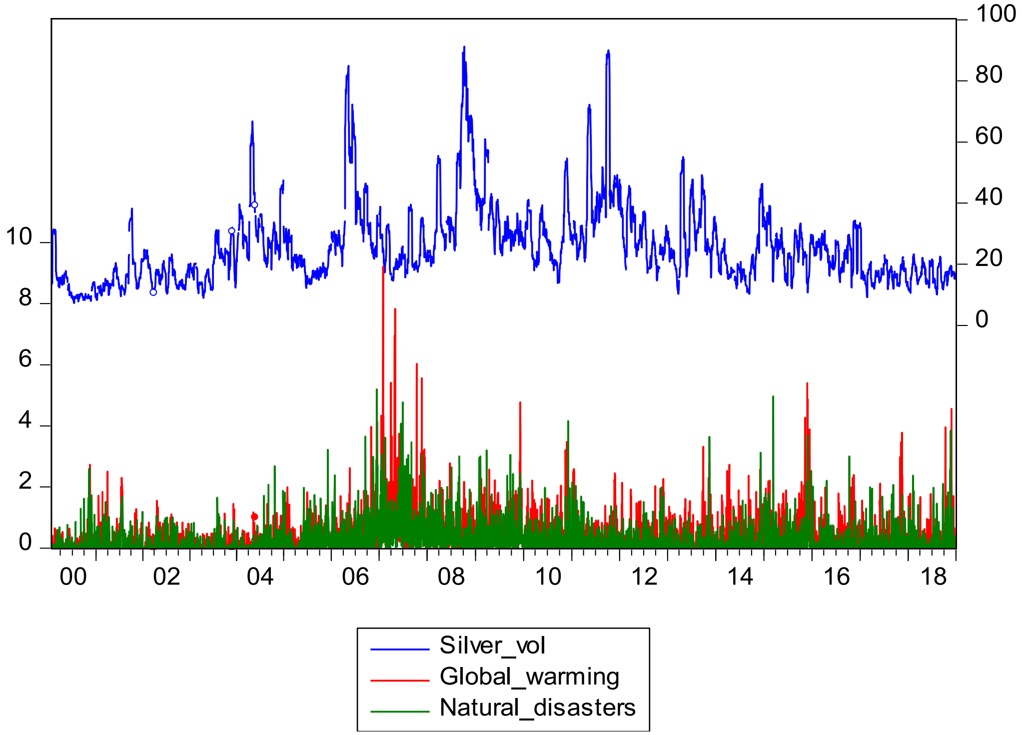

Fig. 4: Silver Realized Volatility and Physical Climate Risk

3. Methodology

We formulate a predictive model for the climate-gold nexus following the approach of Westerlund and Narayan (2012, 2015). The theoretical motivation for the nexus hinges on the risk-return hypothesis where investment in risky assets is influenced by market or systemic risk and in this case, we isolate climate risk in a way that any resulting bias is accommodated in the estimation process. Thus, the theoretical attraction to the approach of Westerlund and Narayan (2012, 2015) is motivated by its ability to deal with inherent bias in the estimation process such as endogeneity bias, persistence and conditional heteroscedasticity typical of financial series that are more prone to volatility (Narayan and Bannigidadmath, 2015) compared to Lewellen (2004) approach, which only accounts for persistence in the forecast model (Olofin et al., 2020).

Furthermore, it is evident in the methodological literature that accounting for breaks, when found to be significant, tends to improve the forecast outcomes (Salisu et al., 2019a, 2019b). Thus, to improve the forecast accuracy of our predictive model, we account for possible structural breaks within the model framework owing to the observed spikes in the series (see Figures 1 and 2) while we equally test the significance of these spikes using the Bai and Perron (2003) test (the results of the structural break test are reported in Table A3 in the appendix).[9] This test allows for up to five breaks in the predictive regressions. We write our predictive model as:

$$gp_t^{RV} = \alpha + \gamma gp_{t-1}^{RV} + \beta clm_{t-1} + \varphi(clm_t - \rho clm_{t-1}) + \sum_{i=1}^{5} \lambda_i brk_{i,t} + \varepsilon_t \qquad (1)$$

where gp_t^{RV} (the predictand) expressed in its natural log form is the computed return volatility for gold price and clm_t (the predictor) is the reference climate change factor. We include gp_{t-1}^{RV} to capture the inherent persistence effect in the dependent variable (which is close to one, see Table 1). Also, $\varphi(clm_t - \rho clm_{t-1})$ is a persistence-adjustment term that is introduced to resolve the inherent persistence effect in clm_t and endogeneity bias that may have occurred due to model misspecification. α is the regression intercept; β is the bias-corrected coefficient (see Westerlund and Narayan, 2012, 2015) and it is a measure of predictability or otherwise of climate risk. The underlying testable null hypothesis is that $H_o : \beta = 0$, wherein the rejection of this

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[9] We favour this test over other structural break tests such as Narayan and Popp (2010) and Narayan and Liu (2015) as the former deals more with shifts in regression models rather than in the individual series.

hypothesis favours the predictability of climate change risk for the return volatility of gold price, or no predictability, if the outcome is otherwise. Similarly, λ_i is the coefficient associated with the break dummy; while ε_t is a zero mean idiosyncratic error term. As for the breaks as shown in equation (1), $brk_{i,t} = 1 \ \forall \ t \geq$ break date and zero, otherwise. As previously noted on the nature of our series, we also control for conditional heteroscedasticity effect by pre-weighting equation (1) with the inverse of the standard deviation of the regression residuals and then estimating the resulting equation with the Ordinary Least Squares (OLS) esimator. The process leading to this is the feasible quasi GLS estimator by Westerlund and Narayan (2012, 2015). This approach to predictability has been found efficient in circumventing the difficulties associated to returns predictability in the empirical literature (see for example, Narayan and Gupta, 2015; Salisu, Ademuyiwa and Isah, 2018; Zhang, Narayan and Devpura, 2021).

Following the above, we extend our estimation to include the out-of-sample forecast evaluation of our proposed model in equation (1) relative to two benchmark models, namely: random walk with drift and random walk without drift where both are restricted versions of equation (1). The former takes the form $gp_t^{RV} = gp_{t-1}^{RV} + \varepsilon_t$, whereas the latter mirrors $gp_t^{RV} = \alpha + gp_{t-1}^{RV} + \varepsilon_t$. Thereafter, we subject the forecast of our predictive model to statistical evaluations using both relative Root Mean Square Error (RMSE) and Clark & West (2007) [C-W] tests. Meanwhile, we adopt 75:25 data split option for in-sample predictability and out-of-sample forecast evaluation, respectively[10] as we consider 30-, 60- and 120-days ahead forecast horizons. The relative RMSE is computed as $1-\left(RMSE_{UR}/RMSE_R\right)$ where $RMSE_{UR}$ is the RMSE for the unrestricted model (our Climate risk-based model as in equation (1)) and $RMSE_R$ is the RMSE for the restricted model whether random walk with and without drift. It should be noted that a positive value of the relative RMSE implies that the climate risk-based model outperforms the restricted model while the opposite holds for a negative value. Nevertheless, since the significant difference in the forecast errors of the two competing models cannot be statistically established with the relative RMSE, we opt for the C-W test for this purpose. Attraction to C-W

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[10] There is no empirical stipulation on what should inform the choice of data split, as such, studies have adopted different split ratio with outcomes not influenced by choice of splits (see for example, Narayan and Gupta, 2015; Salisu etal., 2019b).

test lies in its appropriateness for nested models unlike the familiar Diebold and Mariano (1995) and its variants which can only be used for non-nested models. Thus, the C-W test is a two-step procedure where the first step involves generating the forecast series from equation (2):

$$\hat{f}_{t+k} = \left(Act_{t+k} - Fit_{r,t+k}\right)^2 - \left[\left(Act_{t+k} - Fit_{ur,t+k}\right)^2 - \left(Fit_{r,t+k} - Fit_{ur,t+k}\right)^2\right] \qquad (2)$$

where t is for the in-sample period; k is for the out-of-sample period; $\left(Act_{t+k} - Fit_{r,t+k}\right)^2$ and $\left(Act_{t+k} - Fit_{ur,t+k}\right)^2$ are the squared errors for the restricted and the unrestricted models, respectively with Act being for the actual series and Fit for the fitted values of Act; and $\left(Fit_{r,t+k} - Fit_{ur,t+k}\right)^2$ is introduced into the C-W test to correct for any noise associated with the larger (unrestricted) model's forecast. The second step involves regressing the $\hat{f}_{t+k}$ on a constant and drawing inference based on the resulting t-statistic of the constant. The null hypothesis of a zero coefficient is therefore rejected if the t-statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test).

4. Results and Discussion

4.1. Predictability and Forecast Evaluation

Our objective is to evaluate the predictability of transition and physical risk for the return volatility of gold. The role of gold has an effective portfolio diversifier and inflation hedge is well documented in the literature. A number of studies have also explained the impact of climate risk coverage on financial assets and energy prices. However, we suspect that news coverage on climate change may not necessarily impact return volatility of gold directly but rather through its impact on other financial assets for which gold serves as a hedge. Taking stocks and oil as examples, which both have a negative relationship with climate risk, we hypothesize that when spikes in climate risk cause the return volatilities of these assets to decline, rational investors tend to de-invest and seek a safe haven in gold which consequently drives up its return volatility.

From our predictability result in Table 2, our outcome is mixed. On one hand, we find that true to our hypothesis, return volatility of gold appears to have a positive and significant relationship with transition risk. Our result implies that regardless of the political party in power in the US, climate policies will most likely continue to drive net investment in the direction of gold. Instinctively, this means that in period of high global climate uncertainty, investor confidence in gold soars and level of investment is expected to increase, and conversely, when climate uncertainty declines, investors invest in other profit maximizing assets at the opportunity cost of gold. Likewise, for international summit, the result shows that clamour for an increased tax on climate damaging activities positively affects the return volatility of gold, albeit at a lower magnitude than US climate policy on climate change. This conforms with the findings of Faccini, Matin, and Skiadopoulos (2021), that US climate policy as indexed provides information only on very short-term transition risk while international summits are informative over a longer time horizon, hence, the disparity in the magnitude of both variables is observed. On the other hand, our result shows that the relationship between return volatility of gold and physical risk is significantly negative. In other words, while transition risks may not necessarily have an adverse effect on gold return volatility, physical risk does. Occurrence of natural disasters especially, adds to the average cost of mining gold. Incidence of wildfire, flood or earthquake in mining areas puts mining activities on hold and adds to the cost involved in setting up mining equipment or replacing new ones. In some instances, it also reduces the availability of gold for mining by rendering mining areas permanently inaccessible. Similarly, news of the impact of global warming often makes licencing authorities more reluctant to granting mining licences and willing to impose higher taxes on gold mining activities. Both of our results also confirm the findings of Karmakar, Gupta, Çepni & Rognone, (2022) who establish that the trading volume of gold has a positive and significant relationship with physical risk while this is not necessarily the case under transition risks. This outcome may imply that return volatility as an inverse relationship with trade volume. Simply put, as market risk (return volatility) decreases, trade volume increases.

For the sake of robustness, we repeat our analysis for another precious metal, silver. The outcome shows that our result is not sensitive to the choice of precious metals. Thus, regardless of whether gold or silver is considered, the direction of relationship with both transition and physical risk is not markedly affected.

Next, we examine the forecast performance of our proposed model against the two benchmark models (randomwalk without drift and randomwalk with drift). We evaluate the forecast performance for both in-sample and out-of-sample forecast horizons using the relative root mean square error (RMSE) and Clark and West (2007) pairwise forecast measures. A model (the proposed model, whose RMSE is the numerator) is said to outperform another model (benchmark, whose RMSE is the denominator) if the ratio, when subtracted from one, yields a positive value. However, the CW test on the other hand provides the formal procedure for ascertaining the statistical significance of the difference in the observed forecast errors. A positive and significant value of the constant parameter in the CW test regression indicates better forecast performance of the model with the adjusted-MSE relative to the one without adjustment (see the Methodology section for details). The relative RMSE and CW test results for the randomwalk with and without are summarized in Tables 3-6 (and the actual RMSE values are reported in Tables A1 and A2).

Against this background, from our result in Table 3, we find that our proposed model outperforms the random walk without drift benchmark model for both in-sample and out-of-sample forecast (consistently for all its horizons). We obtain similar results for random walk with drift as presented in Table 4. However, we observe that of the two categories of climate risk used in our model, transition risk appears to predict more accurately the return volatility of gold compared to physical risk in both forecast evaluations. This implies that in modelling the return volatility of gold, transition risk plays more significant role than physical risk although both are important. Likewise, we run the analysis using the return volatility of silver and we obtain similar result. These findings have important implications for the global economy. One, it implies that investment in gold market will be largely influenced by the amount of news coverage on US climate change policy and international summits on climate change. Therefore, more investment in gold can be expected during the term of a Democratic Party president than a republican president in the US. For instance, gold price first experienced a surge in over a decade ago, March 2008, when it crossed the $1000 per ounce mark and continued to rise to about $1600 per ounce in 2016. This period of time coincided with the two terms of the Democratic Party president, Barack Obama whose administration is notable for drastic climate change policies, most significant amongst which is the decision in 2013 to change from crude oil to shale oil, and cut down on crude oil import and the signing of Paris agreement in 2016. Similarly, gold price has also experienced a gradual rise since in the beginning of the Biden administration, most prominently after it rejoined the Paris Agreement. Two, while an increase in coverage of transition risk may imply higher gold return volatility and subsequently, an increase in investment level, physical risks pose a great challenge to investment, regardless of which party is in power and for this reason not all climate risk is not good news for investors.

Furthermore, to adjudge the outcome of our out-of-sample forecast as significant or not, we employ the Clark and West pairwise correlation test as discussed earlier. The outcome shows that our result is significant for both cases of randomwalk with and without drift. We find significantly positive coefficients across the specified periods, and as such we ascertain that these outperformances are sustained regardless of the forecast horizon.

Table 2: Predictability results

		Gold	**Silver**
Transition risk $\left[CLIM_{t-1}\right]$	**Climate Policy**	0.0289*** [3.6442]	0.0431*** [9.3854]
	Int'l Summit	0.0006*** [7.1847]	0.0001*** [2.7361]
Physical risk $\left[CLIM_{t-1}\right]$	**Natural Disasters**	-0.0082*** [-114.13]	-0.0034*** [-29.017]
	Global Warming	-0.0033*** [-47.448]	-0.0007*** [-9.3908]

Note: The results presented in the table are for the predictability of climate risk for the return volatility oil and natural gas. ***, ** and * indicate statistical significance at 1%, 5% and 1% levels. Results in square brackets [ ] are the t-statistics.

Table 3: Forecast Evaluation using Relative RMSE where Random Walk without drift is the benchmark model

Variable/Climate risk factors		In-Sample		Out-of-Sample					
				h=30		**h=60**		**h=120**	
		Gold	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**
Transition risk	**Climate Policy**	0.8070	0.7791	0.8075	0.7805	0.8059	0.7811	0.8048	0.7829
	Int'l Summit	0.8164	0.7902	0.8174	0.7915	0.8171	0.7920	0.8178	0.7937
Physical risk	**Natural Disasters**	0.8218	0.7920	0.8228	0.7932	0.8226	0.7937	0.8234	0.7954
	Global Warming	0.8181	0.7926	0.8191	0.7938	0.8188	0.7943	0.8195	0.7959

Note: The results presented in the table are for the forecast evaluation of the (climate risk-based) model and the restricted (random model without drift) using the Relative RMSE. Given that relative RMSE is computed as $1-\left(RMSE_{UR}/RMSE_{R}\right)$ where $RMSE_{UR}$ is for the unrestricted while $RMSE_{R}$ is for the restricted, a positive value of the relative RMSE implies the superior performance of the unrestricted model over the restricted model while the reverse holds for a negative value.

Table 4: Forecast Evaluation using Relative RMSE where Random Walk with drift is the benchmark model

Variable/Climate risk factors		In-Sample		Out-of-Sample					
				h=30		**h=60**		**h=120**	
		Gold	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**
Transition risk	**Climate Policy**	0.0712	0.1909	0.0680	0.1903	0.0590	0.1904	0.0459	0.1894
	Int'l Summit	0.1165	0.2316	0.1161	0.2308	0.1130	0.2309	0.1093	0.2296
Physical risk	**Natural Disasters**	0.1427	0.2382	0.1425	0.2373	0.1398	0.2373	0.1366	0.2359
	Global Warming	0.1248	0.2402	0.1243	0.2395	0.1215	0.2395	0.1178	0.2381

Note: The results presented in the table are for the forecast evaluation of the unrestricted (climate risk-based) model and the restricted (random walk model with drift) using the Relative RMSE. Given that relative RMSE is computed as $1-\left(RMSE_{UR}/RMSE_{R}\right)$ where $RMSE_{UR}$ is for the unrestricted while $RMSE_{R}$ is for the restricted, a positive value of the relative RMSE implies the superior performance of the unrestricted model over the restricted model while the reverse holds for a negative value.

Table 5: Forecast Evaluation using C-W test where Random Walk without drift is the benchmark model

Variable/Climate risk factors		In-Sample		Out-of-Sample					
				h=30		**h=60**		**h=120**	
		Gold	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**
Transition risk	**Climate Policy**	100.18[a]	88.384[a]	100.88[a]	89.202[a]	101.76[a]	90.049[a]	103.38[a]	91.661[a]
	Int'l Summit	102.33[a]	85.353[a]	103.13[a]	86.169[a]	104.05[a]	86.999[a]	105.81[a]	88.607[a]
Physical risk	**Natural Disasters**	102.01[a]	85.580[a]	102.84[a]	86.399[a]	103.77[a]	87.230[a]	105.54[a]	88.835[a]
	Global Warming	102.49[a]	85.679[a]	103.30[a]	86.491[a]	104.22[a]	87.322[a]	105.98[a]	88.925[a]

Note: The results presented in the table are for the forecast evaluation of the unrestricted (climate risk-based) model and the restricted (random walk model without drift) using the Clark and West (2007) [C-W] test. The t-statistics are presented for this purpose and [a], [b] and [c] indicate statistical significance at 1%, 5% and 10% levels, respectively. Our proposed (climate risk-based) predictive model has better forecast performance than the benchmark model when the t-statistic is positive and statistically significant, otherwise, the benchmark model is considered superior.

Table 6: Forecast Evaluation using C-W test where Random Walk with drift is the benchmark model

Variable/Climate risk factors		In-Sample		Out-of-Sample					
				h=30		**h=60**		**h=120**	
		Gold	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**	**Gold**	**Silver**
Transition risk	**Climate Policy**	22.469^{a}	41.663^{a}	22.427^{a}	41.547^{a}	21.642^{a}	41.687^{a}	20.750^{a}	41.630^{a}
	Int'l Summit	28.142^{a}	39.909^{a}	28.110^{a}	39.810^{a}	27.771^{a}	39.916^{a}	27.361^{a}	39.871^{a}
Physical risk	**Natural Disasters**	29.090^{a}	40.484^{a}	29.058^{a}	40.380^{a}	28.813^{a}	40.481^{a}	28.495^{a}	40.430^{a}
	Global Warming	28.070^{a}	40.416^{a}	28.039^{a}	40.316^{a}	27.744^{a}	40.419^{a}	27.338^{a}	40.367^{a}

Note: The results presented in the table are for the forecast evaluation of the unrestricted (climate risk-based) model and the restricted (random walk model without drift) using the Clark and West (2007) [C-W] test. The t-statistics are presented for this purpose and ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively. Our proposed (climate risk-based) predictive model has better forecast performance than the benchmark model when the t-statistic is positive and statistically significant, otherwise, the benchmark model is considered superior.

4.2 Economic Significance

As discussed in the methodology section, we conduct an additional analysis following Campbell and Thompson (2008) to evaluate the economic significance of our result. In doing this, first, we construct a utility function modelling climate-related risk in the gold market whose activities are impacted by such risks. We begin by formulating a predictive model for excess returns where the climate risks are separately observed.

$$GPXRET_{t+1} = \alpha + CLIM_{t} + \varepsilon_{t+1} \qquad (3)$$

where $GPXRET_{t+1}$ represents the excess gold price returns (obtained as the actual gold price returns less the risk free rate using the US three-month treasury bill rate as a proxy) evaluated at period $t+1$; α denotes the unconditional mean of $GPXRET_{t+1}$; $CLIM_{t}$ is for the climate-related risk (whether physical risk or transition risk)[11] being observed by investors in the gold market; and ε_{t+1} is a disturbance term with zero mean and constant variance, σ_{ε}^{2}. However, where the investors do not observe climate-related risk the model reduces to:

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[11] Given the way the model is constructed, we expect the predictor series to meet the stochastic properties of zero mean and constant variance. The unit root test results further confirm the existence of these properties (see Table A4 in the appendix).

$$GPXRET_{t+1} = \alpha + \varepsilon_{t+1} \quad (4)$$

Note that equation (4) is the traditional historical average model. Theoretically, the utility function for a profit maximizing investor is usually defined as:

$$Max\ U\left(r_{gold}\right) = E\left(r_{gold}\right) - (\vartheta/2)Var\left(r_{gold}\right) \quad (5)$$

where $U\left(r_{gold}\right)$ is the utility derivable from investing in gold market computed as the expected return from gold investment (denoted as $E\left(r_{gold}\right)$) less the associated risks measured as $(\vartheta/2)Var\left(r_{gold}\right)$ where ϑ is the relative risk aversion. If the investors in the gold market observe $CLIM_t$, they will have average excess returns on gold investment computed as (see, Campbell and Thompson (2008) for technical details):

$$\overline{r}_{CLIM} = \left(\frac{1}{\vartheta}\right)\left(\frac{\alpha^2 + \sigma^2_{CLIM}}{\sigma^2_{\varepsilon}}\right) \quad (6)$$

where $\overline{r}_{gold}$ is the average excess return conditional on $CLIM_t$. However, if the investors do not observe $CLIM_t$, average excess return on gold investment becomes:

$$\overline{r} = \left(\frac{1}{\vartheta}\right)\left(\frac{\alpha^2}{\sigma^2_{\varepsilon} + \sigma^2_{CLIM}}\right) \quad (7)$$

where $\overline{r}$ is the average excess return that is not conditional on $CLIM_t$. Unlike in equation (6) where σ^2_{CLIM} is part of the numerator components since the climate-related risk is directly observed and therefore does not contribute to the gold market risk (σ^2_{ε}), however, it (σ^2_{CLIM}) is part of the denominator components in equation (7) as it contributes to σ^2_{ε}.

In Tables 7 and 8, we present the results of equations (6) and (7) for different values of relative risk aversion, $\vartheta = 3$ and $\vartheta = 8$, respectively. We compute our result for the different climate-related risks including the full sample (combination of in-sample and out-of-sample periods) and in-sample periods where the out-of-sample includes up to 120 days ahead forecast. Our findings about the utility gains of observing climate-related risks in the gold market are as follows. First, investors that observe climate risks in the valuation of gold price returns based on equations (3) and (7) are more likely to derive higher returns relative to their counterparts that fail to account for the mentioned risks (as in equations 4 and 7). In other words, climate risks contain predictive content that can help profit-oriented investors to make higher returns. Second, we observe that for most of the climate-risk, investors tend to derive higher utility gains at lower coefficients of relative risk aversion regardless of whether investors directly observe it or not. Third, the observed outcomes in one and two are consistent for silver market and across the various measures of climate risk. Finally, like the predictability results, we also notice that higher economic gains are obtained when the transition risks are observed relative to the physical risks.

Table 7: Economic Significance results [$\vartheta = 3$]

	Gold		**Silver**	
Climate Policy				
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.239	3.256	0.238	3.255
Out-of-Sample	0.252	3.337	0.251	3.335
Int’l Summit				
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.218	1.863	0.219	1.869
Out-of-Sample	0.227	1.951	0.227	1.957
Natural Disaster				
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.483	1.436	0.483	1.437
Out-of-Sample	0.504	1.478	0.504	1.479
Global Warming				
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.490	1.731	0.490	1.732
Out-of-Sample	0.487	1.771	0.486	1.772

Note: The restricted model excludes the climate-related factors while the Unrestricted accommodates them. We use the symbol ϑ to denote the relative risk aversion.

Table 8: Economic Significance results [ϑ = 8]

	Gold		Silver	
	Climate Policy			
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.241	3.280	0.089	1.221
Out-of-Sample	0.254	3.359	0.094	1.251
	Int'l Summit			
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.082	0.699	0.082	0.701
Out-of-Sample	0.085	0.732	0.085	0.734
	Natural Disaster			
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.181	0.538	0.181	0.539
Out-of-Sample	0.189	0.554	0.189	0.555
	Global Warming			
	Restricted	**Unrestricted**	**Restricted**	**Unrestricted**
In-Sample	0.184	0.649	0.184	0.649
Out-of-Sample	0.183	0.664	0.182	0.664

Note: The restricted model excludes the climate-related factors while the Unrestricted accommodates them. We use the symbol ϑ to denote the relative risk aversion.

5. Conclusion

The existential threat posed by climate risks to global economic activity is well acknowledged. However, what remains unclear in the literature is the facet of climate risk containing predictive content for specific financial assets. This explains our attraction to the climate risk indices developed by Faccini et al. (2021, 2022) which broadly classify these indices into physical (comprising US climate policy & International summit) and transition risks (comprising natural disaster and global warming) unlike most of the other climate risk measures that ignore these important distinctions. Consequently, we examine the in-sample and out-of-sample predictability of the climate risk measures for the gold return volatility. The underlying motivation of this study is rooted in the rapidly growing global awareness on the environmental impact of climate change and its implication for the future of the economic and financial ecosystem. Besides, investor preference for information on business risk in the valuation of investment securities underscores our consideration of gold market risk. For profit maximizing investors, risk assessment is an integral part of investment decisions and therefore our analyses offer both academic and investment perspectives to the climate-gold nexus as we also include possible utility gains of observing climate risk in gold market.

We present the summary of our findings as follows. First, from our result, we observe that transition risk and physical risk impact volatility of gold return differently. We suspect that while transition risk may have a negative impact on gold return volatility, physical risk positively impacts the market. In the case of transition risk, both its components, US climate policy and international summit, have positive and significant effect on volatility of gold return. Thus, an increase in the news coverage of transition risk appears to heighten gold market risk. Quite often, when there is an increase in news coverage around US climate policy pronouncement or call for tax on carbon emissions to be increased, investment in other non-ecofriendly assets such as oil and gas declines. This decline usually results in a boost for investment in gold given its hedging properties and thus increasing the volatility in the gold market. This indirect path illustrates the channel through which transition risk may impact volatility of gold return. However, the negative impact of physical risk suggests that global warming and natural disaster (which constitute its components) may have cost implication among other things on gold prices. Incidence of wildfire, flood or earthquake in mining areas puts mining activities on hold and adds to the cost involved in setting up mining equipment or replacing new ones.

Second, out-of-sample predictability result reveals that our proposed model outperforms other competing benchmark models such as the randomwalk with and without drift, although the model performs stronger with transition risk. This confirms our hypothesis that indeed, both transition and physical risks contain predictive content for gold return volatility. For the sake of robustness, we substitute gold for silver in our model and conduct similar analyses for the volatility of silver return. The outcome is consistent with earlier reported results for gold confirming that our model is not commodity-sensitive. Finally, the outcome of our utility function shows that accounting for transition risk over physical risks guarantees higher economic gains than otherwise. Hence, profit maximizing investors are encouraged to pay attention to the global sentiments on climate risk, with more attention on transition risk given its ability to impact the volatility formation of gold to a large extent. Furthermore, the outcome of this study will help in design of optimal portfolio that can hedge against climate risk. Likewise, practitioners and academics who are constantly involved in the analyses of energy markets may find our proposed model and the various conclusions insightful, particularly in terms of producing more accurate forecasts when analysing the risks associated with the energy market. In terms of policy, we encourage policy makers, especially in the United States, to be more pragmatic in their approach towards combatting climate change and avoid unnecessary sensationalism of climate issues, as this has a tendency to adversely impact the assets market. Future research may consider whether the above findings can be generalized to include other commodities like agricultural commodities and precious metals.

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Table A1: Actual RMSE for both the restricted and the unrestricted models [In-sample]

Variable/Climate risk factors		Gold	Silver
Transition risk	**Climate Policy**	0.3682	0.3768
	Int'l Summit	0.3503	0.3577
Physical risk	**Natural Disasters**	0.3399	0.3547
	Global Warming	0.3470	0.3537
Random Walk	**Random walk without drift**	1.9079	1.7055
	Random walk with drift	0.3965	0.4656

Note: The results presented in the table are for the RMSE of the unrestricted (climate risk-based) model and the restricted (random walk model without drift). Note that the lower the RMSE value, the better the forecast performance.

Table A2: Actual RMSE for both the restricted and the unrestricted models [Out-of-Sample]

Variable/Climate risk factors		Out-of-Sample					
		h=30		h=60		h=120	
		Gold	Silver	Gold	Silver	Gold	Silver
Transition risk	**Climate Policy**	0.3682	0.3756	0.3714	0.3751	0.3746	0.3738
	Int'l Summit	0.3492	0.3568	0.3501	0.3563	0.3498	0.3553
Physical risk	**Natural Disasters**	0.3388	0.3538	0.3395	0.3533	0.3391	0.3523
	Global Warming	0.3460	0.3528	0.3467	0.3523	0.3465	0.3513
Random Walk	**Random walk without drift**	1.9124	1.7110	1.9140	1.7131	1.9195	1.7217
	Random walk with drift	0.3950	0.4639	0.3947	0.4633	0.3927	0.4611

Table A3: Structural Break points

		Gold	Silver
Transition risk	**Climate Policy**	12/18/2002 12/19/2005 4/30/2009 4/11/2013 3/9/2016	6/26/2003 3/4/2008 12/23/2010 1/15/2014
	Int'l Summit	12/18/2002 12/21/2005 4/30/2009 4/11/2013 3/9/2016	6/26/2003 3/18/2008 1/15/2014
Physical risk	**Natural Disasters**	12/18/2002 12/21/2005 4/30/2009 4/11/2013 3/9/2016	6/26/2003 3/4/2008 12/23/2010 1/15/2014
	Global Warming	12/18/2002 12/30/2005 4/30/2009 4/11/2013 3/9/2016	6/26/2003 3/4/2008 12/23/2010 1/15/2014

Note: To obtain the break dates, we first estimate equation (1) (excluding the break term) with OLS, that is, $ENER_t^{RV} = \alpha + \tau ENER_{t-1}^{RV} + \beta CLIM_{t-1} + \gamma(CLIM_t - \rho CLIM_{t-1}) + \mu_t$ and thereafter, we apply the Bai and Perrون (2003) test to determine the number of breaks as well as the corresponding dates.

Table A4: Unit roots test

Variable	Test	Level			Difference		
		None	Intercept	Trend	None	Intercept	Trend
Gold	ADF	-3.3910^{a}	-8.2012^{a}	-8.2177^{a}	-64.2262^{a}	-64.2195^{a}	-64.2133^{a}
	PP	-3.5690^{a}	-8.4642^{a}	-8.4838^{a}	-64.4187^{a}	-64.4121^{a}	-64.4064^{a}
Silver	ADF	-3.0365^{a}	-6.8248^{a}	-6.8236^{a}	-62.6861^{a}	-62.6794^{a}	-62.6736^{a}
	PP	-3.1180^{a}	-6.9218^{b}	-6.9244^{a}	-63.1012^{a}	-63.0954^{a}	-63.0896^{a}
Climate Policy	ADF	-1.1223	-2.1394	-2.5774	-12.5110^{a}	-12.4817^{a}	-12.4524^{a}
	PP	-2.4585^{a}	-4.9855^{a}	-5.3236^{a}	-29.4227^{a}	-29.3639^{a}	-29.3509^{a}
Natural Disaster	ADF	-1.0544	-5.5385^{a}	-5.5304^{a}	-10.4468^{a}	-10.4212^{a}	-10.4093^{a}
	PP	-2.7992^{a}	-5.2096^{a}	-5.2049^{a}	-48.4176^{a}	-48.7163^{a}	-73.4885^{a}
Int'l Summit	ADF	-1.5440	-2.5884^{c}	-2.5702	-13.9738^{a}	-13.9372^{a}	-13.9256^{a}
	PP	-2.1582^{a}	-4.0820^{a}	-4.0548^{a}	-25.9964^{a}	-25.9157^{a}	-26.1913^{a}
Global Warming	ADF	-2.4239^{b}	-4.2013^{a}	-4.2778^{a}	-10.7925^{a}	-10.7620^{a}	-10.7234^{a}
	PP	-3.7594^{a}	-6.4111^{a}	-6.6579^{a}	-37.3616^{a}	-37.8272^{a}	-37.6261^{a}

Note: ADF test is the Augmented Dickey Fuller test and PP is Phillip Perron. $^{a,\,b}$ and ^{c} indicate 1%, 5% and 10% level of significance respectively. The null hypothesis for ADF and PP tests is that the series has unit root. Rejection of this null indicates that the series is stationary.