Resources Policy 82 (2023) 103438

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Climate risks and predictability of the trading volume of gold: Evidence from an INGARCH model[☆]

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ARTICLE INFO

JEL classification:
C22
C53
Q02
Q54

Keywords:
Climate risks
Precious metals
Forecasting
Trading volumes
Count data
INGARCH

ABSTRACT

We investigate whether text-based physical or transition climate risks forecast the daily volume of gold trade contracts. Given the count-valued nature of gold volume data, we employ a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (IN-GARCH) model with a climate-related covariate. We detect that physical risks have a significant predictive power for gold volume at 5- and 22-day-ahead horizons. Additionally, from a full-sample analysis, it emerges that physical risks positively relate with gold volume. Combining these findings, we conclude that gold hedges physical risks at 1-week and 1-month horizons. Similar results hold for platinum and palladium, but not for silver.

1. Introduction

Climate change is associated with two types of risks, namely physical and transition. Physical risk involves losses and costs due to factors such as rising temperatures, higher sea levels, storms, and floods or wildfires. Transition risk, on the other hand, is associated with a costly switchover to a low-carbon economy, usually prompted by climate policy changes, emergence of competitive green technologies, and shifts in consumer preferences. Due to the uncertainty surrounding the future course of climate change and its economic implications, every future scenario includes climate-related financial risks. Climate-related risks have been shown to adversely affect a large number of asset classes, including currencies, equities, fixed-income securities, and real estate, as well as financial institutions (Battiston et al., 2021; Giglio et al., 2021; Bonato et al., 2022), generally raising the stress on the entire financial system (Flori et al., 2021).

Due to heightened distress in the financial system arising from climate risks, gold, given its well-established "safe haven" properties (Boubaker et al., 2020; Bouri et al., 2022), may play a key role. Gold, in fact, serves as an investment vehicle that offers portfolio diversification and/or hedging benefits during periods of financial turmoil, which can also arise from climate-related events. In such instances of "bad news" and due to the information-seeking actions of traders, gold returns and its volatility are therefore expected to increase due to higher trading volumes, capturing information flows emanating from its higher demand (Wang and Yau, 2000; Batten and Lucey, 2010; Baur, 2012). As a support of this theory, recent studies show a positive relationship between gold returns, and its volatility, with climate risks (Cepni et al., 2022; Gupta and Pierdzioch, 2022).

Specifically, on one hand Cepni et al. (2022) show, inter alia, using an asymmetric dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (ADCC-GARCH) model, that the time-varying correlation between gold (and to some extent platinum and silver) is generally positive relative to physical and transition risks associated with climate change, possibly due to higher trading activity in the gold market, though green bonds also tended to stand

[☆] We would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours. The first author's research is partially supported by National Science Foundation DMS, USA 2124222.

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https://doi.org/10.1016/j.resourpol.2023.103438
Received 10 October 2022; Received in revised form 15 February 2023; Accepted 26 February 2023
Available online 13 March 2023

out in terms of acting as a hedge. On the other hand, Gupta and Pierdzioch (2022) use variants of the Heterogeneous Autoregressive Realized Volatility (HAR-RV) model to examine the out-of-sample predictive value of climate-risk factors for the realized volatility of gold price returns (as well as the realized volatility of for other metal price returns namely, copper, palladium, platinum, and silver). The authors estimate the HAR-RV models using not only ordinary least squares, but also three different popular shrinkage estimators. They find that climate-risk factors improve the accuracy of out-of-sample forecasts prices at a monthly and, in some cases, also at a weekly forecast horizon, which is likely a result of the positive effect of climate risks on trading volume, given gold's safe haven characteristic.

In light of the underlying intuition that climate risks can be associated with higher returns and volatility of gold prices due to increased trading volumes, this paper contributes to the broader green finance literature[1] by documenting the direct effect of climate risks on the volume of traded contracts of gold. This is in contrast to the two studies mentioned above, which focused on returns and volatility and indirectly address the issue of trading volumes. In this regard, we resort to an out-of-sample forecasting exercise over the daily period of 3rd January, 2005 to 29th October, 2021, rather than an in-sample predictability analysis mainly for two reasons. First, under a statistical perspective, forecasting is considered to be a more robust test of predictability in terms of both models and predictors (Campbell, 2008). Second, accurate real-time forecasting of volumes (based on the information content of climate risks), which is known to lead returns and volatility, should be of much more value to traders and investors in the gold market, relative to in-sample evidence, in the timely pricing of related derivative securities and for devising portfolio-allocation strategies. Realizing the count-valued nature of the time series data on the trading volume of gold, our econometric framework is a log-linear Poisson integer-valued GARCH (INGARCH) model with predictors, which in turn are textual analysis-based metrics of physical or transition risks associated with climate. While the focus is on gold, given that recent studies have also depicted the possible safe haven characteristic for palladium, platinum, and silver (Lucey and Li, 2015; Salisu et al., 2021), we also consider the role of climate risks as predictors of the trading volumes of these three different precious metals, over the same period as gold. Our main findings suggest that gold acts as a hedge for physical risks at one-week and one-month-horizons, a result that we detect also for platinum and, to a lesser extent, for palladium but not for silver. In other words, we find that gold is best suited to hedge climate risks, particularly the physical one, when compared to other precious metals. To the best of our knowledge, this is the first paper using count data-based models to forecast daily volumes of precious metals relying on the information contained in physical and/or transition climate risks to provide a direct test of the safe haven characteristic of this asset-class. The remainder of the paper is organized as follows: Section 2 presents the methodology, Section 3 discusses the data, Section 4 is devoted to the empirical findings, and Section 5 concludes the paper.

2. Methodology

Consider the following autoregressive model for count time-series inspired from the GARCH model of Bollerslev (1986)

$$y_t|y_{t-1}, y_{t-2}, \ldots \sim Poi(\lambda_t) \tag{2.1}$$
$$\lambda_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_1 \lambda_{t-1}$$

where $y_1, \ldots, y_t$ is an observed general non-negative integer-valued time-series, λ_t stands for the shape parameter of the Poisson distribution used to model the marginal distribution of y_t, and α_0, α_1, and β_1 are attached coefficients used to model the intercept, autoregressive and the GARCH lag contributions, respectively. In the literature, such models are named INGARCH(1,1) and have become a state-of-the-art framework for analysing count data (Davis et al., 2021). In the forecasting exercises we carry out in this paper, we choose trading volume as this count time-series. The parameter space for these basic model in (2.1) models is restricted due to constraints of positivity, and this gives rise to the following log-linear INGARCH model, making the parameter space relatively more unrestricted:

$$y_t|y_{t-1}, y_{t-2}, \ldots \sim Poi(\lambda_t) \tag{2.2}$$
$$log(\lambda_t) = \alpha_0 + \alpha_1 log(1 + y_{t-1}) + \beta_1 log(\lambda_{t-1})$$

Bringing in covariates or predictors, we obtain the following log-linear Poisson INGARCH(1,1) model:

$$y_t|y_{t-1}, y_{t-2}, \ldots \sim Poi(\lambda_t) \tag{2.3}$$
$$\log(\lambda_t) = \alpha_0 + \alpha_1 \log(1 + y_{t-1}) + \beta_1 \log(\lambda_{t-1}) + \boldsymbol{\eta}^T X_t$$

where X_t is the matrix of covariates and η is a matrix of suitable dimensions corresponding to the coefficients attached to these covariates. To ensure stationarity and stability of such univariate models, it is necessary to assume that: $-1 < \alpha_1 + \beta_1 < 1$.

We use the prediction routine in the `tscount` package in R (Liboschik et al., 2017) to produce forecasts. In short, this method chooses a roll-over forecasting scheme such that, to predict y_{n+1} based on $y_1, \ldots, y_n$, the simple conditional expectation is used, and to predict y_{n+2} based on $y_1, \ldots, y_{n+1}$, the simple conditional expectation is still used, but the unknown y_{n+1} is replaced by $\hat{y}_{n+1}$ based on the previous computation, and so on for $y_{n+3}, \ldots$.

We judge the quality of future the $h-$step aggregated forecast, i.e. $y_{n+1} + \cdots + y_{n+h}$ for different values of h through a pseudo-out-of-sample evaluation metric. More specifically, we follow the following steps:

- Predict $FWC_{i,h} = \hat{y}_{i+m} + \cdots + \hat{y}_{i+m+h-1}$ using the log-linear INGARCH `tsglm` predict routine with covariate(s) based on pairs (y_j, X_j) $j = i, \ldots, i+m-1$;
- $FWOC_{i,h} = \hat{y}_{i+m} + \cdots + \hat{y}_{i+m+h-1}$ using the log-linear INGARCH `tsglm` predict routine without covariates based on pairs (y_j) $j = i, \ldots, i+m-1$;
- Next we compare the two forecasted series $FWC_{\{\},h}$ and $FWOC_{\{\},h}$ by the means of Clark and West (2007a) test.

3. Data

Our climate risks data are sourced from Bua et al. (2022) and consist of a daily Physical Risk Index (PRI) and Transition Risk Index (TRI). These two novel climate risk indicators are the result of a text-based approach which combines the term frequency-inverse document frequency and the cosine-similarity techniques expanding on the work of Engle et al. (2020). Specifically, the authors first group various scientific texts on climate change by topic, either involving physical or transition risk, to obtain two documents that, if digested, provide a comprehensive understanding of the physical and transition climate risks. The authors then use these climate risks-related documents to feed their text-based algorithms, and search the same structured information within a corpus of (European) news sourced by Reuters News. As output, they obtain two distinct time series, so-called "concerns", roughly representing the news media attention towards physical and transition risks, which we denote as $\mathrm{CONCERN}_{\mathrm{PR}}$ and $\mathrm{CONCERN}_{\mathrm{TR}}$, respectively. As a final step, the authors model the climate risks series, PRI and TRI, as autoregressive order one (AR(1)) residuals of the concerns series in order to capture shocks and innovations in physical and transition risks.

We use these measures of climate risks because the proposed measures, originated from advanced climate vocabularies, exhibit several advantages with respect to previous studies. They, for instance, embed multiple dimensions of these risks without discarding relevant aspects resulting in complete climate risks indicators, which can enhance studies on the financial implications of climate risks. The PRI includes both acute and chronic physical risks like floods, extreme weather

[1] See Giglio et al. (2021) and Hong et al. (2020) for an exhaustive review.

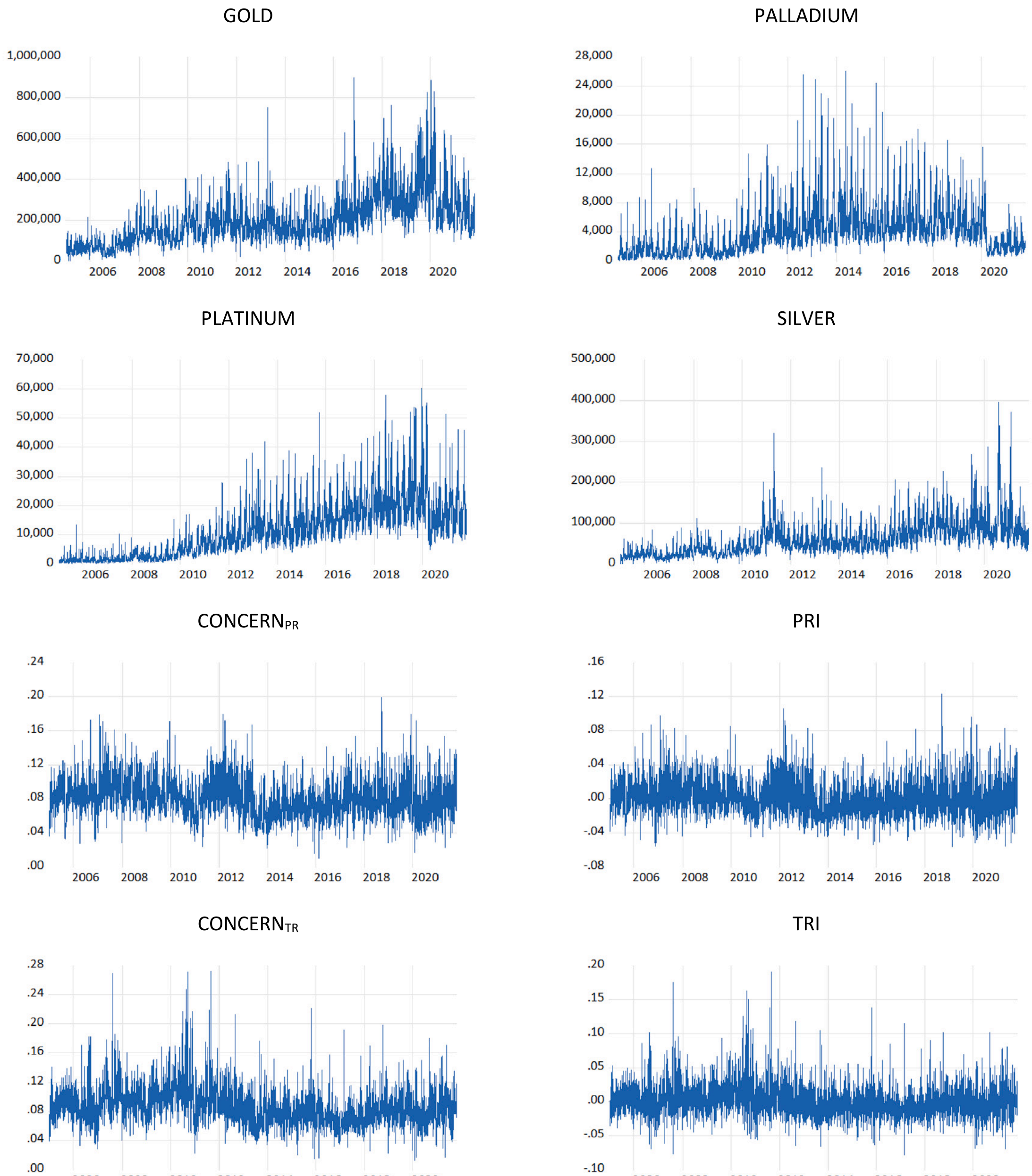


Fig. 1. Time series plot of climate risk measures and count data variables.

events, permafrost thawing, and sea level rise, as well as issues about climate adaptation actions, and other physical risk-averse effects like the loss in biodiversity. The TRI, on the other hand, includes news on regulations and measures to curb greenhouse gas (GHG) emissions, news concerning the costs associated with the transition to a greener economy, and news discussing the advances of technological innovation and renewable energies to reach, for example, net-zero emissions targets. Bua et al. (2022) also perform commonality tests to assess the actual degree of overlap of the two indicators and conclude that both PRI and TRI carry relevant individual information.

Daily data on the volume of traded contracts of the top four precious metals, namely gold, palladium, platinum and silver, are downloaded from Bloomberg. Our analysis covers the period of 3rd January, 2005 to 29th October, 2021, i.e., 4245 daily observations. Note that, the start and end dates of our samples are purely driven by the availability of data on the climate risks predictors. All the variables of interest have been plotted in Fig. 1 to provide a graphical summary of their evolution over time for the sample period considered in this paper. Additionally, Table 1 provides the summary statistics of the dataset utilized. The values of the trading volume of gold clearly provides evidence of its importance relative to the other precious metals. In fact, gold exhibits always higher trading volume values than those of palladium, platinum, and silver for each statistic (minimum, 1st, median, mean, 3rd, and maximum). For what concerns the climate data, we observe that the news media attention towards physical (transition) climate risk issues has ranged from a minimum of 1% of the daily news corpus to a maximum of 20% (27%), during our sample period, with an average coverage of 7.9% (8.5%) and relatively low standard deviation. In other words, the 7.9% (8.5%) of the news is about physical (transition) risk, every day on average. Also the physical risk and transition risk shocks

Table 1
Summary statistics for the datasets.

	Min	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
Gold	1906	115846	172079	193588	251474	897219	113625.10
Palladium	74	1563	3332	3853	5066	26103	3089.505
Platinum	144	3165	9682	11152	16243	60162	9260.03
Silver	515	32001	51689	59891	78340	397177	39714.07
$\text{CONCERN}_{\text{PR}}$	0.01002	0.06461	0.07684	0.07914	0.09122	0.1994	0.02183646
$\text{CONCERN}_{\text{TR}}$	0.01346	0.06833	0.08168	0.08514	0.09915	0.27199	0.02558997
PRI	−0.0559951	−0.0134595	−0.002206	0.0004774	0.0119388	0.1225069	0.02069075
TRI	−0.0782058	−0.0140185	−0.0024852	0.0004997	0.0123734	0.1907316	0.02333305

(PRI and TRI) are positive on average, indicating a general unexpected discussion around climate change issues that has reached a maximum of 12% for physical risk and 19% for transition risk.

4. Empirical results

4.1. Preliminary analysis of the relationship between trading volumes and climate risks

Before we proceed to the formal forecasting exercise, we check if indeed climate risks positively impact the trading volume of gold, as expected in light of the gold's "safe haven" ability to hedge, e.g., climate risks. For this purpose, we utilize a time-varying approach analogue to that of Eq. (2.3).[2] Fig. 2 shows the time-varying effect, t-statistics, of $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$ on the trading volume of gold (top row), palladium (second row), platinum (third row), and silver (bottom row). An overall positive (negative) sign would indicate that climate risks indeed increase (decrease) the trading volume of precious metal confirming (contrasting) the underlying hypothesis. Considering gold, such effect is generally positive in a statistically significant manner under physical risks, $\text{CONCERN}_{\text{PR}}$, while this is not necessarily the case under transition risks, $\text{CONCERN}_{\text{TR}}$.[3] Qualitatively similar results are drawn for palladium and platinum, and, to a lesser extent, for silver. This finding is expected to a certain degree, given the underlying nature of these two risks, with the effects of physical risks likely to be felt immediately on the stress of the financial system. In light of this evidence related to the sign of the effect of climate risks, we would want to put relatively more reliance on the forecasting accuracy of gold volumes emanating from physical rather than transition risks in the process of validating the safe haven nature of gold, and other precious metals.

4.2. Climate risks and forecasting results of trading volumes of precious metals

Recall our INGARCH model (2.3) with the included predictors. Note that, since our goal is to determine if the predictors are playing a significant role in improving the forecasts, we are in the premise of comparing forecasts of two nested models, with the null model stating that the absence of a predictor does a statistically comparable forecasting job as the model with the covariate. We use the Clark and West test (CW henceforth) (Clark and West, 2007b). In short, this test does not directly compare the Mean Square Error (MSE) for the two models, as the null model will always be beaten in such a situation. Instead, we adjust for the additional covariate factor and then run the comparison between the adjusted-MSE using the test.

Table 2
CW p-values for forecasts of trading volumes of precious metals based on metrics of climate risks for $m = 500$.

	Gold	Palladium	Platinum	Silver
$h = 1$ day				
$\text{CONCERN}_{\text{PR}}$	0.1516	0.0338	0.5155	0.0185
$\text{CONCERN}_{\text{TR}}$	0.7873	0.0080	0.9380	0.5576
PRI	0.3311	0.0115	0.4822	0.0054
TRI	0.3779	0.0977	0.5424	0.0860
$h = 5$ days				
$\text{CONCERN}_{\text{PR}}$	0.0036	0.8603	0.0985	0.6815
$\text{CONCERN}_{\text{TR}}$	0.3347	0.2218	0.5316	0.3738
PRI	0.0037	0.5924	0.0024	0.0078
TRI	0.0338	0.1357	0.0373	0.0000
$h = 22$ days				
$\text{CONCERN}_{\text{PR}}$	0.0071	0.8689	0.0139	0.5256
$\text{CONCERN}_{\text{TR}}$	0.8585	0.8147	0.3902	0.1232
PRI	0.0146	0.5540	0.0037	0.0062
TRI	0.5376	0.6736	0.2331	0.0001

In Table 2, we present the p-values of the CW test derived based on a rolling-window estimation of $m = 500$, i.e., approximately two years of data points, implying that the out-of-sample period starts from the tumultuous time associated with the beginning of the global financial crisis, with the models estimated on a rolling window-basis till the end of the sample period. Fig. A.1 in the Appendix shows the estimated $\alpha_1 + \beta_1$ curve (see (2.3) for context) for the model involving the volume of traded contracts of gold without covariates (No covariates), with both $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$ (Concern covariates), and with both PRI and TRI (Risk covariates) over the entire sample period. The time varying estimates of $\alpha_1 + \beta_1$ are consistently lower than one ensuring that the stationarity assumption is reasonable for each window, and hence that our predictive model is a stable one to draw valid inferences from.

The forecasts are conducted for three horizons of h=1, 5, and 22, corresponding to a one-day-, one-week-, and one-month-ahead. We find that $\text{CONCERN}_{\text{PR}}$ produces statistically superior forecasting gains relative to the benchmark model at h=5 and 22 for the trading volume of gold, which in turn are also reflected in the PRI results for these corresponding forecasting horizons. TRI is also found to produce statistical forecasting gains for gold trading volumes at h=5, but the corresponding PRI produces a much lower p-value, indicating that physical risk is therefore a better predictor. In sum, while we do not find evidence of forecastability of gold volume one-day-ahead, we do so at one-week- and at one-month-ahead, and that too from the physical risks component of climate change. Given the positive time-varying

[2] The time-varying log-linear Poisson INGARCH(1,1) model can be described as: $y_t | y_{t-1}, y_{t-2}, \ldots \sim Poi(\lambda_t)$, with $\log(\lambda_t) = \alpha_0(t/n) + \alpha_1(t/n)\log(1 + y_{t-1}) + \beta_1(t/n)\log(\lambda_{t-1}) + \boldsymbol{\eta}(\mathbf{t}/\mathbf{n})^T X_t$. For the estimation of the parameter functions $(\alpha_0(\cdot), \alpha_1(\cdot), \beta_1(\cdot), \boldsymbol{\eta})$, we employ a kernel-based technique padded on quasi-maximum likelihood estimation as in Karmakar et al. (2022). In this regard, we use the rectangular kernel $K(x) = I(-1 \le x \le 1)$ and bandwidth $b_n = m/n$ to remain consistent with our forecasting set-up, which in turn assumes stationarity of the last m observations.

[3] Using PRI and TRI instead of $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$, yielded, not surprisingly, similar observations, with the results available upon request from the authors.

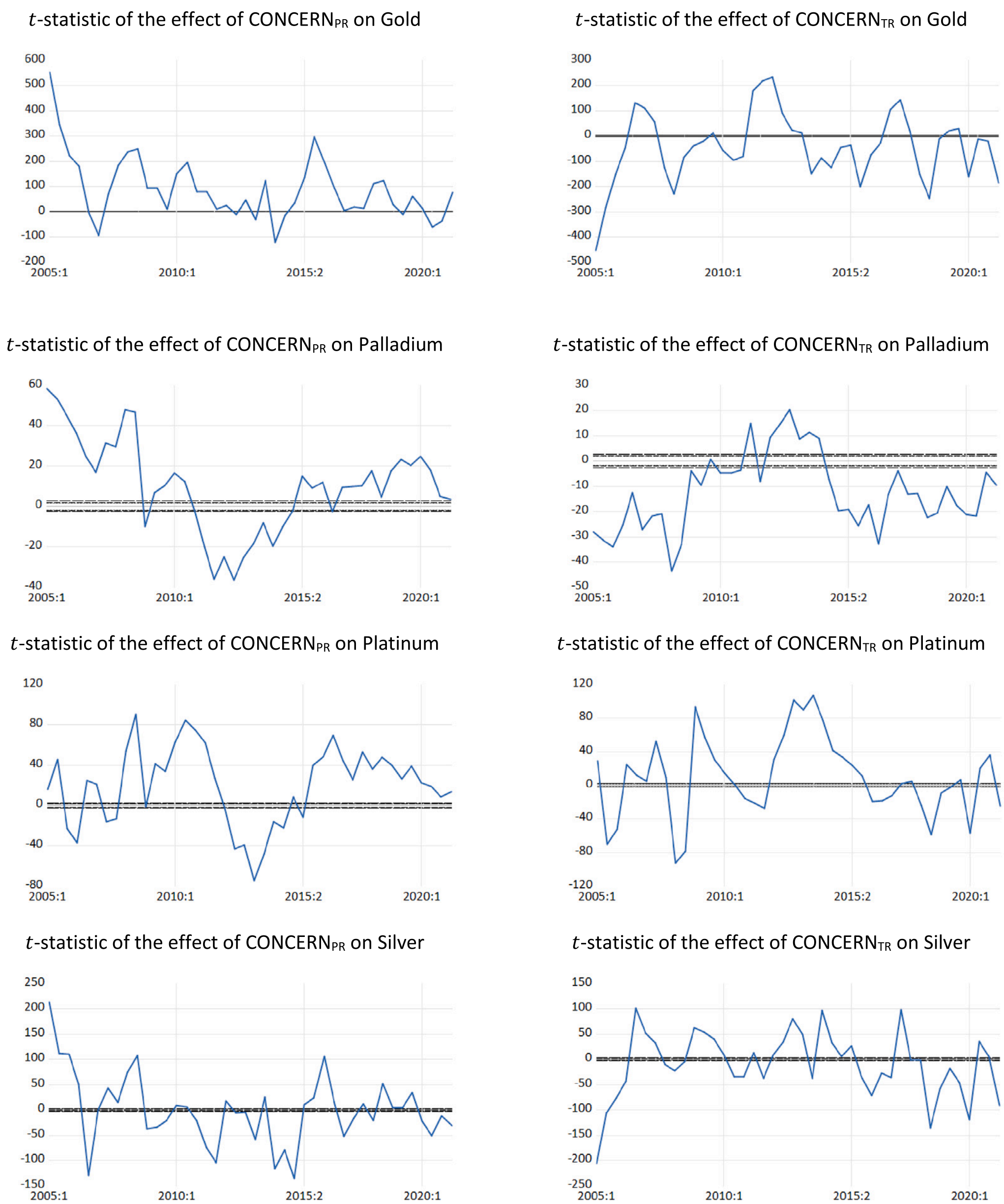


Fig. 2. Climate risks' time-varying effect on the volume of contracts traded for precious metals.
Note: The dotted lines correspond to *t*-values at the significance levels of 1% (+/−2.575), 5% (+/−1.96) and 10% (+/−1.645).

impact of such risks on the trading volume of gold (as shown in Fig. 2), we can say that gold acts as a hedge against physical risks at one-week- and one-month-horizons.

To understand how the model performs over time in forecasting the trading volume of gold based on the information content of $CONCERN_{PR}$ and $CONCERN_{TR}$, as well as of PRI and TRI, the squared prediction errors at $h = 1$, 5, and 22 over the entire out-of-sample period are plotted in Fig. A.2 in Appendix. As it can be seen, the predictive performance of climate risks is shown to be exceptionally good with low squared forecast errors, which, however, increases during the COVID-19 outbreak period particularly at the one-month-ahead horizon, suggesting lesser predictive influence of climate risks. This should not come as a surprise as the uncertainty and attention during this extraordinary period were primarily related to health risks, with declines in climate-related risks also depicted in Fig. 1. Understandably, the associated rise in gold trading activity and volumes during this phase could be tied more to the pandemic rather than to issues of climate change, hence making the prediction errors relatively larger, which however tend to fall again post-2020. In other words, barring exceptional episodes, gold can be considered to act as a hedge against climate risks.

Turning now to the other three precious metals, we find that statistically superior forecasting gains for palladium emanating from both physical and transition risks are obtained at $h = 1$, while this holds for both $h = 5$ and $h = 22$ for platinum. As far as silver is concerned, accurate forecasting is derived from the climate risks-related metrics for all three horizons, with a stronger effect obtained under transition risks compared to physical ones, especially when one compares the *p*-values associated with TRI and PRI. In light of the underlying time-varying relationship between the trading volumes of palladium, platinum, and silver with climate risks, we tend to conclude that while the former two, especially platinum, can hedge climate risks, silver, with its volume being negatively impacted, is not necessarily well-suited to play the role of a safe haven relative to physical and transition risks.

It is interesting to see that the shorter rolling window of $m = 125$ leads to stronger forecasting performance for gold volume at $h = 1$ compared to $h = 5$, as reported in Table A.1 of the appendix. This may be due to the fact that the shorter window is more sensitive to recent changes and fluctuations in the market, which are reflected in the increased predictability at the shorter horizon. However, it is important to note that using a shorter window may come at a cost of reduced precision in the estimates. Nonetheless, the overall conclusion of the importance of climate risks in predicting gold volume remains consistent across both rolling windows. The same pattern is observed for platinum and silver as well.[4]

5. Conclusions

In this paper, we forecast the daily volume of trade contracts of gold based on the information contained in text-based metrics of physical or transition risks associated with climate change. In light of the count-valued nature of the time series data of gold volume, we use a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (INGARCH) model involving a specific-type of climate change-related predictor. Based on daily data covering the period 3rd January, 2005 to 29th October, 2021, we detect statistically superior forecasting gains for gold volume emanating from physical risks at one-week- and at one-month-ahead horizons, but not for one-day-ahead. Given the underlying positively evolving impact of such risks on the trading volume of gold, obtained from a full-sample analysis using a time-varying INGARCH model, we conclude that gold acts as a hedge against physical risks of climate change at one-week- and one-month-horizons. This finding is also documented for platinum and, to a lesser extent, for palladium, but not for silver.

Our findings suggest that gold, platinum, and palladium can be included in a multi-asset portfolio to hedge against the physical aspect of climate risks. Climate risks are known to negatively impact the risk of financial assets, and including these metals in a portfolio could help reduce that risk. However, the study finds that silver may not be as effective in this regard. It is important to note that these findings are based on the relationship between climate risks and trading volume, and further research would be needed to fully explore the implications for portfolio design and risk management. Nonetheless, the results provide some guidance for investors looking to build portfolios that can weather the impact of climate risks on financial markets. Additionally, future research can, e.g., further explore the climate risks forecasting ability for the trading volume of other assets though to offer financial hedge against the climate change, such as "green" or "environmental, social, and governance (ESG)" assets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

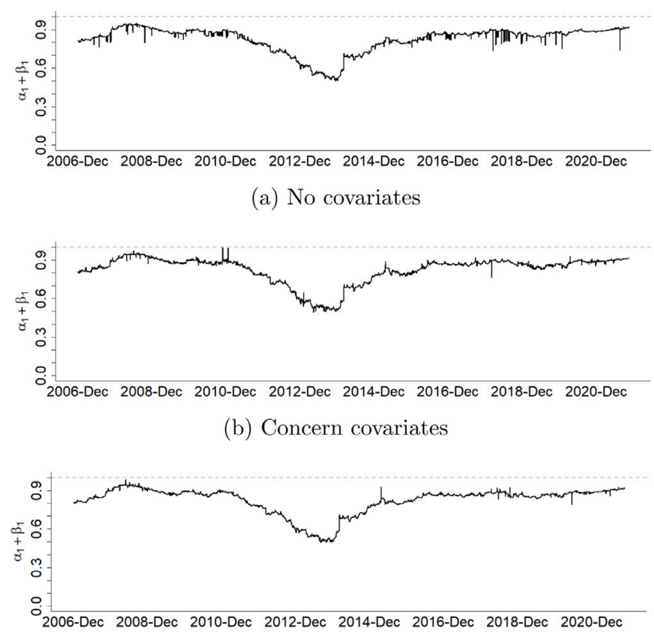
Data is available from Bloomberg with access.

Appendix

See Table A.1.

Table A.1
CW *p*-values for forecasts of trading volumes of precious metals based on metrics of climate risks for $m = 125$.

	Gold	Palladium	Platinum	Silver
h = 1 *day*				
$CONCERN_{PR}$	0.0796	0.3033	0.7291	0.0053
$CONCERN_{TR}$	0.0756	0.7169	0.7144	0.0204
PRI	0.0001	0.0045	0.0061	0.0053
TRI	0.0094	0.0048	0.0405	0.0716
h = 5 *days*				
$CONCERN_{PR}$	0.4466	0.978	0.8103	0.0461
$CONCERN_{TR}$	0.3661	0.7342	0.8445	0.0247
PRI	0.191	0.6689	0.0735	0.2382
TRI	0.0219	0.4338	0.046	0.005
h = 22 *days*				
$CONCERN_{PR}$	0.0484	0.0121	0.0039	0.1656
$CONCERN_{TR}$	0.0499	0.0354	0.2066	0.0269
PRI	0.1711	0.1775	0.2992	0.4842
TRI	0.074	0.2822	0.023	0.1029



(a) No covariates

(b) Concern covariates

(c) Risk covariates

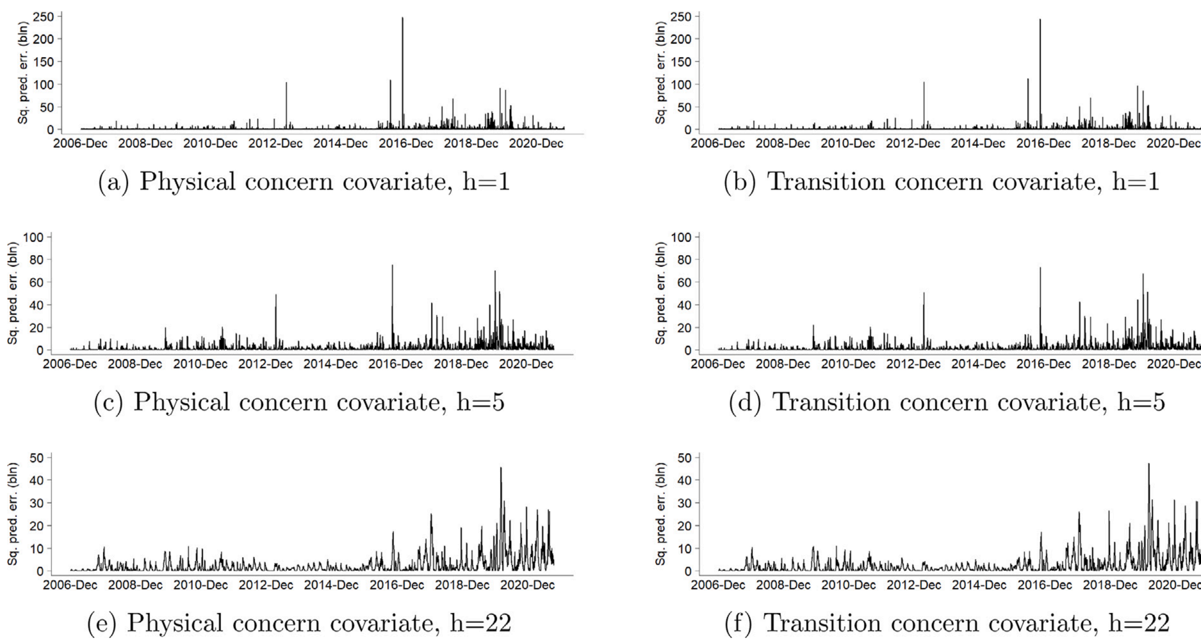
Fig. A.1. Estimated $\alpha_1 + \beta_1$ for the Gold data in three scenarios: (a) without covariates, (b) Concern covariates together, (c) Risk covariates together.

[4] As part of additional analysis, we collected 5-minute interval intraday price data of these four precious metals from Bloomberg, and computed daily counts of positive and negative log-returns. The idea in this instance is that if gold and the other three metals are indeed safe haven, then climate risks should be able to predict relatively more accurately the positive rather than the negative counts, as an indication of being a hedge against such risks. For this exercise, we consider the period of 1st May, 2018 to 29th October, 2021, with the start date concentrated around the peak date (19th September, 2018) of the physical risk metrics, with which gold trading volumes were shown to be, in general, positively related. As shown in Table A.2 of the Appendix, gold is the only case, compared to the three other precious metals, whereby not only physical, but also transition risks, tend to accurately forecast positive returns only at h = 1- and 5-day ahead. Note that, in light of the small sample size of 973 observations, we use a rolling-window of 125 days to obtain our results. These findings, in turn, confirm that gold is indeed best-suited among precious metals to hedge climate risks.

Table A.2
CW p-values for forecasts of count of negative and positive log-returns of precious metals based on metrics of climate risks.

	Gold(-)	Gold(+)	Palla(-)	Palla(+)	Plati(-)	Plati(+)	Silv(-)	Silv(+)
h = 1 *day*								
$CONCERN_{PR}$	0.5133	0.1752	0.4537	0.3530	0.2563	0.3806	0.5666	0.1382
$CONCERN_{TR}$	0.5863	0.0974	0.0005	0.2325	0.3271	0.2477	0.1800	0.4095
PRI	0.5582	0.3376	0.0911	0.1454	0.5451	0.1769	0.4141	0.0584
TRI	0.2448	0.0101	0.0000	0.0001	0.0979	0.0295	0.0055	0.0599
h = 5 *days*								
$CONCERN_{PR}$	0.8809	0.0614	0.6413	0.1020	0.8995	0.0616	0.6656	0.0231
$CONCERN_{TR}$	0.8519	0.1150	0.6939	0.0674	0.5921	0.4680	0.9058	0.2494
PRI	0.4390	0.1400	0.4699	0.0724	0.8710	0.0501	0.3262	0.0173
TRI	0.6106	0.0978	0.1539	0.0061	0.4548	0.2239	0.7337	0.1364
h = 22 *days*								
$CONCERN_{PR}$	0.9741	0.4987	0.3309	0.6267	0.7895	0.5719	0.9915	0.1660
$CONCERN_{TR}$	0.8692	0.5397	0.8881	0.1097	0.7086	0.8413	0.9736	0.6213
PRI	0.8479	0.8827	0.8744	0.7016	0.9113	0.6123	0.8696	0.1650
TRI	0.8745	0.7585	0.8180	0.0985	0.6247	0.9366	0.9059	0.5890

Note: − or + corresponding to the name of a precious metal indicates the case of negative or positive count of log-returns; Palla, Plati and Silv stand for Palladium, Platinum and Silver respectively.



(a) Physical concern covariate, h=1
(b) Transition concern covariate, h=1
(c) Physical concern covariate, h=5
(d) Transition concern covariate, h=5
(e) Physical concern covariate, h=22
(f) Transition concern covariate, h=22

Fig. A.2. Time-varying squared prediction error for gold series with climate concern covariates for different horizon lengths.

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