University of Pretoria

Department of Economics Working Paper Series

Climate Risks and Predictability of the Trading Volume of Gold: Evidence from an INGARCH Model

Sayar Karmakar
University of Florida
Rangan Gupta
University of Pretoria
Oğuzhan Çepni
Copenhagen Business School and Central Bank of the Republic of Turkey
Lavinia Rognone
The University of Manchester

Working Paper: 2022-41
September 2022

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Climate Risks and Predictability of the Trading Volume of Gold: Evidence from an INGARCH Model

Sayar Karmakar[1], Rangan Gupta[2], Oğuzhan Çepni[3], Lavinia Rognone[4]

Abstract

We investigate the ability of textual analysis-based metrics of physical or transition risks associated with climate change in forecasting the daily volume of trade contracts of gold. Given the count-valued nature of gold volume data, our econometric framework is a log-linear Poisson integer-valued generalized autoregressive conditional heteroskedasticity (INGARCH) model with a particular climate change-related covariate. We detect a significant predictive power for gold volume at 5- and 22-day-ahead horizons when we extend our model using physical risks. Given the underlying positively evolving impact of such risks on the trading volume of gold, as derived from a full-sample analysis using a time-varying INGARCH model, we can say that gold acts as a hedge against physical risks at 1-week and 1-month horizons. Such a characteristic is also detected for platinum, and to a lesser extent, for palladium, but not silver. Our results have important investment implications.

JEL Classification: C22; C53; Q02; Q54.

Keywords: Climate Risks; Precious Metals; Forecasting; Trading Volumes; Count Data; INGARCH.

[1]Department of Statistics, University of Florida, 230 Newell Drive, Gainesville, FL, 32601, USA. Email address: sayarkarmakar@ufl.edu

[2]Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email address: rangan.gupta@up.ac.za

[3]Copenhagen Business School, Department of Economics, Porcel16A, Frederiksberg DK-2000, Denmark; Central Bank of the Republic of Turkey, Haci Bayram Mah. Istiklal Cad. No:10 06050, Ankara, Turkey. Email address: oce.eco@cbs.dk.

[4]Alliance Manchester Business School, The University of Manchester, Booth St W, Manchester M15 6PB, UK. Email address: lavinia.rognone@manchester.ac.uk.

Declaration of interest: none.

1. Introduction

Climate change is associated with two types of risks, namely physical and transition. Physical risk involves losses and costs due to, e.g., rising temperatures, higher sea levels, storms, and floods or wildfires. Transition risk is instead 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. Naturally, though the uncertainty around 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 of the entire financial system (Flori et al., 2021).

Due to heightened distress in the financial system arising out of 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, also possibly originated 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 & Yau, 2000; Batten & 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 & Pierdzioch, 2022).

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[5] by documenting the direct effect of climate risks on the volume of traded contracts of gold. 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

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

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 generalized autoregressive conditional heteroskedasticity (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 & Li, 2015; Salisu et al., Forthcoming), 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, result that we detect also for platinum and, to a lesser extent, for palladium but not for silver. 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)

$$y_t | y_{t-1}, y_{t-2}, \cdots \sim Poi(\lambda_t) \tag{2.1}$$

$$\lambda_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_1 \lambda_{t-1}$$

where $y_1, \cdots y_t$ 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 analyzing 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:

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

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

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

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: $0 < \alpha_1 + \beta_1 < 1$.

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 $y_1, \cdots y_n$, the simple conditional expectation is used, and to predict y_{n+2} based on $y_1, \cdots y_{n+1}$, 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 $y_{n+3}, \cdots$.

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) $j = i, \cdots, i + m - 1$;
- $FWOC_{i,h} = \hat{y}_{i+m} + \cdots + \hat{y}_{i+m+h-1}$ using the log-linear INGARCH `tsglm` predict routine without covariates based on pairs (y_j) $j = i, \cdots, i + m - 1$;
- Next we compare the two forecasted series $FWC_{\{\},h}$ and $FWOC_{\{\},h}$ by the means of

Clark & West (2007) 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 $\text{CONCERN}_{\text{PR}}$ and $\text{CONCERN}_{\text{TR}}$, 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 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 Figure 1 to provide a graphical summary of their evolution over time for the sample period considered in this paper.

4. Empirical results

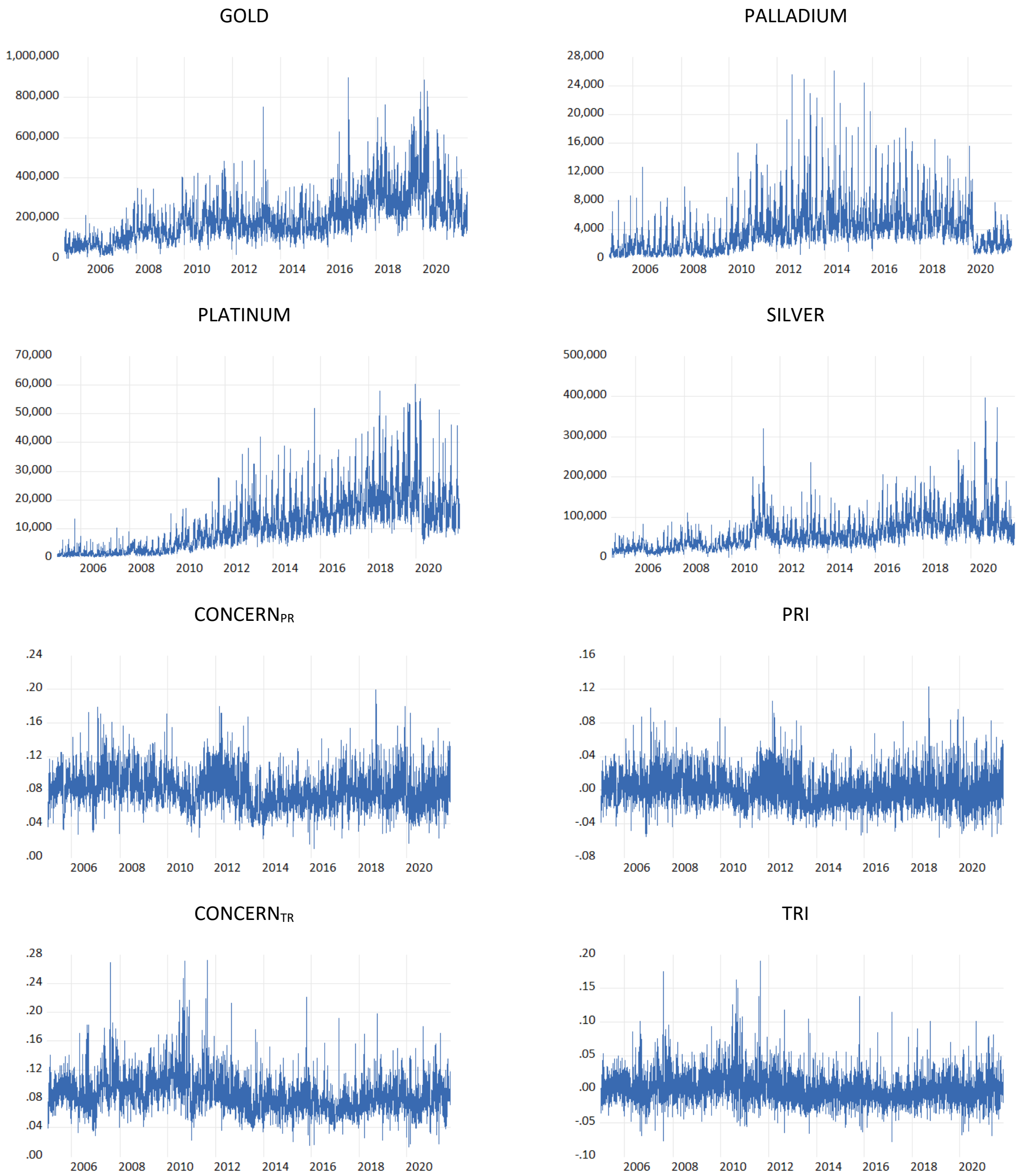
4.1. Preliminary analysis of the relationship between trading volumes and climate risks

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).[6] Figure 2 shows the time-varying effect, t-statistics, of $\mathrm{CONCERN}_{\mathrm{PR}}$ and $\mathrm{CONCERN}_{\mathrm{TR}}$ 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, $\mathrm{CONCERN}_{\mathrm{PR}}$, while this is not necessarily the case under transition risks, $\mathrm{CONCERN}_{\mathrm{TR}}$.[7] 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,

[6]The time-varying log-linear Poisson INGARCH(1,1) model can be described as: $y_t|y_{t-1}, y_{t-2}, \cdots \sim Poi(\lambda_t)$, with $\log(\lambda_t) = \alpha_0(t/n) + \alpha_1(t/n)\log(1+y_{t-1}) + \beta_1(t/n)\log(\lambda_{t-1}) + \eta(\mathbf{t}/\mathbf{n})^T X_t$. For the estimation of the parameter functions $(\alpha_0(\cdot), \alpha_1(\cdot), \beta_1(\cdot), \eta)$, 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.

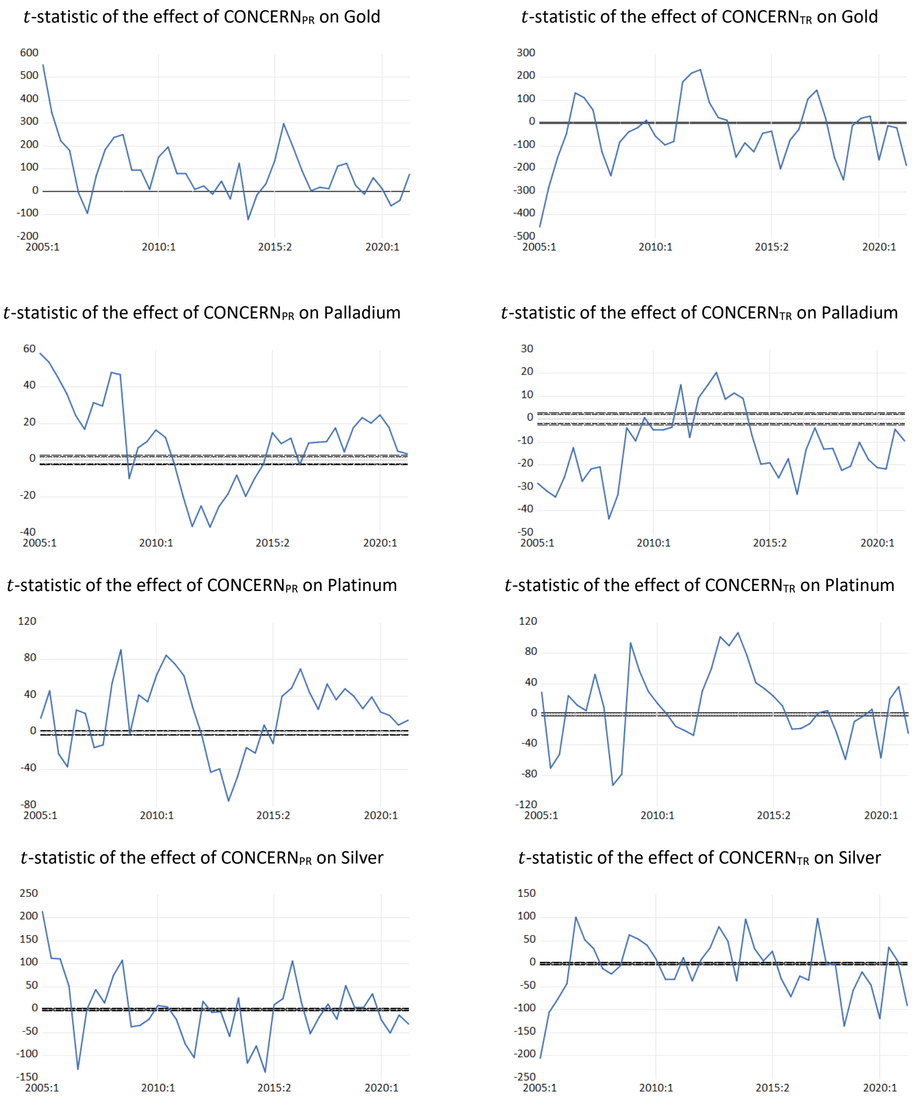
[7]Using PRI and TRI instead of $\mathrm{CONCERN}_{\mathrm{PR}}$ and $\mathrm{CONCERN}_{\mathrm{TR}}$, yielded, not surprisingly, similar observations, with the results available upon request from the authors.

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



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.

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).

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

In Table 1, 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. 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 impact of such risks on the trading volume of gold (as shown in Figure 2), we can say that gold acts as a hedge against physical risks at one-week- and one-month-horizons.

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.[8]

[8] 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 1^st May, 2018 to 29^th October, 2021,

Table 1: CW p-values for forecasts of trading volumes of precious metals based on metrics of climate risks

	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

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 3$^{\text{rd}}$ January, 2005 to 29$^{\text{th}}$ 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.

with the start date concentrated around the peak date ($19^t h$ September, 2018) of the physical risk metrics, with which gold trading volumes were shown to be, in general, positively related. As shown in Table A1 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.

Considering that trading volume is known to lead gold returns and volatility, our results have important investment implications in terms of the design of optimal portfolios. In particular, our findings suggest that gold can be included in a multi-asset portfolio to hedge against the physical aspect of climate risks, known to negatively impact the risk of financial assets. 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.

References

Batten, J. A., & Lucey, B. M. (2010). Volatility in the gold futures market. *Applied Economics Letters*, *17*, 187–190. URL: http://www.tandfonline.com/doi/abs/10.1080/13504850701719991. doi:10.1080/13504850701719991.

Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. *Journal of Financial Stability*, *54*, 100867. URL: https://linkinghub.elsevier.com/retrieve/pii/S1572308921000267. doi:10.1016/j.jfs.2021.100867.

Baur, D. G. (2012). Asymmetric Volatility in the Gold Market. *The Journal of Alternative Investments*, *14*, 26–38. URL: http://jai.pm-research.com/lookup/doi/10.3905/jai.2012.14.4.026. doi:10.3905/jai.2012.14.4.026.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*, 307–327. URL: https://linkinghub.elsevier.com/retrieve/pii/0304407686900631. doi:10.1016/0304-4076(86)90063-1.

Bonato, M., Cepni, O., Gupta, R., & Pierdzioch, C. (2022). Climate risks and realized volatility of major commodity currency exchange rates. *Journal of Financial Markets*, (p. 100760). URL: https://www.sciencedirect.com/science/article/pii/S1386418122000519. doi:https://doi.org/10.1016/j.finmar.2022.100760.

Boubaker, H., Cunado, J., Gil-Alana, L. A., & Gupta, R. (2020). Global crises and gold as a safe haven: Evidence from over seven and a half centuries of data. *Physica A: Statistical Mechanics and its Applications*, *540*, 123093. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378437119317455. doi:10.1016/j.physa.2019.123093.

Bouri, E., Gupta, R., Nel, J., & Shiba, S. (2022). Contagious diseases and gold: Over 700 years of evidence from quantile regressions. *Finance Research Letters*, (p. 103266). URL: https://www.sciencedirect.com/science/article/pii/S1544612322004573. doi:https://doi.org/10.1016/j.frl.2022.103266.

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2022). *Transition versus physical climate risk pricing in European financial markets: A text-based approach*. ECB Working Paper No. 2022/2677. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3860234.

Campbell, J. Y. (2008). Viewpoint: Estimating the equity premium. *Canadian Journal of Economics/Revue canadienne d'économique*, *41*, 1–21. URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2966.2008.00453.x. doi:10.1111/j.1365-2966.2008.00453.x.

Cepni, O., Demirer, R., & Rognone, L. (2022). Hedging climate risks with green assets. *Economics Letters*, *212*, 110312. URL: https://linkinghub.elsevier.com/retrieve/pii/S0165176522000222. doi:10.1016/j.econlet.2022.110312.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*, 291–311. URL: https://linkinghub.

elsevier.com/retrieve/pii/S0304407606000960. doi:10.1016/j.jeconom.2006.05.023.

Davis, R. A., Fokianos, K., Holan, S. H., Joe, H., Livsey, J., Lund, R., Pipiras, V., & Ravishanker, N. (2021). Count Time Series: A Methodological Review. *Journal of the American Statistical Association*, *116*, 1533–1547. URL: https://www.tandfonline.com/doi/full/10.1080/01621459.2021.1904957. doi:10.1080/01621459.2021.1904957.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *Review of Financial Studies*, *33*, 1184–1216. doi:10.1093/rfs/hhz072.

Flori, A., Pammolli, F., & Spelta, A. (2021). Commodity prices co-movements and financial stability: A multidimensional visibility nexus with climate conditions. *Journal of Financial Stability*, *54*, 100876. URL: https://linkinghub.elsevier.com/retrieve/pii/S157230892100036X. doi:10.1016/j.jfs.2021.100876.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate Finance. *Annual Review of Financial Economics*, *13*, 15–36. URL: https://www.annualreviews.org/doi/10.1146/annurev-financial-102620-103311. doi:10.1146/annurev-financial-102620-103311.

Gupta, R., & Pierdzioch, C. (2022). Climate risks and forecastability of the realized volatility of gold and other metal prices. *Resources Policy*, *77*, 102681. URL: https://www.sciencedirect.com/science/article/pii/S0301420722001295. doi:https://doi.org/10.1016/j.resourpol.2022.102681.

Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate Finance. *The Review of Financial Studies*, *33*, 1011–1023. URL: https://academic.oup.com/rfs/article/33/3/1011/5735309. doi:10.1093/rfs/hhz146.

Karmakar, S., Richter, S., & Wu, W. B. (2022). Simultaneous inference for time-varying models. *Journal of Econometrics*, *227*, 408–428. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407621000725. doi:10.1016/j.jeconom.2021.03.002.

Liboschik, T., Fokianos, K., & Fried, R. (2017). tscount : An R Package for Analysis of Count Time Series Following Generalized Linear Models. *Journal of Statistical Software*, *82*. URL: http://www.jstatsoft.org/v82/i05/. doi:10.18637/jss.v082.i05.

Lucey, B. M., & Li, S. (2015). What precious metals act as safe havens, and when? Some US evidence. *Applied Economics Letters*, *22*, 35–45. doi:10.1080/13504851.2014.920471.

Salisu, A., Gupta, R., Ntyikwe, S., & Demirer, R. (Forthcoming). *Gold and the global financial cycle*. International Finance.

Wang, G. H. K., & Yau, J. (2000). Trading volume, bid–ask spread, and price volatility in futures markets. *Journal of Futures Markets*, *20*, 943–970. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/1096-9934%28200011%2920%3A10%3C943%3A%3AAID-FUT4%3E3.0.CO%3B2-8. doi:https://doi.org/10.1002/1096-9934(200011)20:10<943::AID-FUT4>3.0.CO;2-8.

Appendix

Table A1: 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*								
$\text{CONCERN}_{\text{PR}}$	0.5133	0.1752	0.4537	0.3530	0.2563	0.3806	0.5666	0.1382
$\text{CONCERN}_{\text{TR}}$	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*								
$\text{CONCERN}_{\text{PR}}$	0.8809	0.0614	0.6413	0.1020	0.8995	0.0616	0.6656	0.0231
$\text{CONCERN}_{\text{TR}}$	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*								
$\text{CONCERN}_{\text{PR}}$	0.9741	0.4987	0.3309	0.6267	0.7895	0.5719	0.9915	0.1660
$\text{CONCERN}_{\text{TR}}$	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.