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Climate Risks and Real Gold Returns over 750 Years

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Abstract: Using data that cover the annual period from 1258 to 2023, we studied the link between real gold returns and climate risks. We documented a positive contemporaneous link and a negative predictive link. Our findings further show that the predictive link historically gave rise to significant out-of-sample forecasting gains. The positive contemporaneous link is consistent with the view that investors viewed gold as a safe haven in times of elevated climate risks. The negative predictive link, in turn, is consistent with an overshooting scenario in which the real gold price overshot in response to climate risks, only to return subsequently to a lower value. Our findings should provide important implications for investors and policymakers, given that our analysis covered the longest possible data sample involving the gold market, and hence, was independent of any sample selection bias.

Keywords: gold returns; climate risks; forecasting; overshooting

JEL Classification: C22; C32; C53; Q31; Q54

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1. Introduction

Recently, quite a number of studies have studied the link between climate-change-related risks and financial stress [1–5]. The intuition is that abnormal weather conditions constitute a large aggregate risk to the financial system because such conditions have the potential to produce disruptive rare disaster events. Such rare disaster events, in turn, are a key factor impacting the extreme-left-tail of economic states [6–9]. In this regard, the main assumption underlying rare-disaster models is that the entire array of assets in an economy are exposed to an aggregate jump-risk factor [10–12]. Given this, while it is likely that some assets, when studied in cross-section, are more exposed to such a climate-induced jump-risk factor than others, it is also reasonable to expect that such a jump-risk factor would be a major driver of the variation in the tails of individual asset returns from a time-series perspective [13–19], reflecting that a lower productivity and/or a higher stochastic depreciation rate of capital have a negative impact on asset valuations, thus causing a higher risk-premium [20–24]. Taken together, the jump-risk factor stemming from climate risks is likely to raise the level of systematic financial stress due to adverse effects on both the first- and second-moment of asset prices. Moreover, uncertainty surrounding policy measures designed to mitigate the impact of climate risks (that is, climate policy uncertainty) can negatively influence the financial system through various channels, including, for example, the banking system, which plays a major role in determining the stability of financial markets via its role in providing sustainable climate-finance [25].

At the same time, based on the seminal works in [26,27], extensive literature works have analyzed the role of gold as a "safe haven" in times of extreme disruptions and jitters in financial (bonds, (crypto-)currencies, and equities) markets (see [28,29] for comprehensive reviews). In general, the results of these studies showed that market participants regularly invest in gold during episodes of turmoil in (traditional) financial markets, given the ability of gold investments to serve portfolio diversification and/or hedging purposes. In light of this safe-haven property of gold investments, one can hypothesize that climate risks, proxying for rare disaster events, which tend to negatively impact financial asset valuations and enhance associated risks, should carry predictive value for (real) gold prices and/or returns, due to higher trading volumes in the market for this precious metal [30].

In order to investigate this hypothesis formally, we studied the contemporaneous and out-of-sample predictive value of climate risk for real gold returns, where we measured climate risk in terms of the information contained in changes in temperature anomalies (and the corresponding volatility) over the longest possible annual period from 1258 to 2023. In econometric terms, we used a standard linear predictive autoregression model, estimated in a recursive- and rolling-fashion, to account for structural breaks, identified based on explicit statistical tests, in the relationship between real gold returns and climate risks. By considering the longest available sample of historical data on real gold returns and climate risks, we could avoid any possibility of a "sample selection-bias", while drawing a robust predictive inference.

To the best of our knowledge, we are the first to formally relate climate risks to (future) movements of real gold returns over the longest possible data sample covering nine centuries. In the process, our paper adds to three strands of studies: First, we go beyond primarily in-sample-based analyses of climate risks and gold-market movements covering only the last two decades [31–34], given that, from a statistical perspective, out-of-sample forecasting is a relatively stronger test of predictability [35]. Second, we add to the rapidly growing literature on rare disaster events, proxied by large declines in output [36,37], outbreaks of contagious diseases [38], and geopolitical risks [39,40], from a predictive context by relying on extreme weather conditions data to capture rare disaster risks. This is important because climate change has been historically associated with declines in output [41], the spread of infectious diseases [42,43], and conflicts [44,45]. In other words, climate risks should contain catch-all leading information for the other proxies used in this literature. Third, we add to the general forecasting literature (see [46–48] for detailed reviews) on gold returns that has considered a wide array of (behavioral, financial, and macroeconomic) predictors and models using post World War II data (spanning at most half a century), by considering climate risks factors over 750 years of data.

Previewing our findings, we documented a positive contemporaneous link and a negative predictive link, with the latter historically giving rise to significant out-of-sample forecasting gains. The positive contemporaneous link suggests that investors viewed gold as a safe haven in times of elevated climate risks, while the negative predictive link, in turn, is consistent with a scenario in which real gold price returns overshoot in response to climate risks, with the real gold price subsequently reverting back to a lower value. Given the importance of gold as an investment vehicle, as well as a leading indicator of the macroeconomy [49,50], understandably, our results should carry valuable implications for both investors and policymakers. We organize the remainder of the paper as follows: We describe the data we used in our study in Section 2, while we outline our econometric model in Section 3. In Section 4, we present our empirical results. In Section 5, we conclude.

2. Data

We used annual data of nominal prices (in British pounds) of gold starting in 1257 until 2023, with 1257 being the earliest date of data availability. We retrieved the data from MeasuringWorth (see [51] and https://www.measuringworth.com/datasets/gold/ (accessed on 1 August 2024)). We transformed the nominal price of gold into its real value by dividing with the consumer price index (CPI) of the United Kingdom, which we sourced from a database maintained by the Bank of England called "A Millenium of Macroeconomic Data" for the UK (https://www.bankofengland.co.uk/statistics/research-datasets (accessed on 1

August 2024)). Computation of log returns (RGR) implied that our effective sample covered 1258 to 2023 for real gold returns.

The temperature anomaly (TA) data from 1257 until 2019 were acquired from the Climate Lab Book (Open Climate Science; https://web.archive.org/web/20200202220240/https://www.climate-lab-book.ac.uk/2020/2019-years/ (accessed on 1 August 2024)) and then updated from the National Oceanic and Atmospheric Administration (NOAA; https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series (accessed on 1 August 2024)) until 2023. A temperature anomaly occurred either when the recorded temperature was higher than a reference value, such as the long-run average value of temperature (a positive anomaly), or when it was lower than the reference value (a negative anomaly), with the base period being 1961–1990.

As our main metric of climate risks, in line with the literature outlined above, we considered the changes (first-difference) in temperature anomalies (DTA). In addition, like some recent studies (see, for example, refs. [13,22]), we also accounted for the volatility of changes in temperature anomalies in natural logarithms (DTA-VOLA), derived from a standard generalized autoregressive conditional heteroscedasticity (GARCH) model [52] fitted to DTA, as a second measure of climate risks. The rational for the latter was that, while global warming is likely to exert a positive effect on the trend in temperature anomalies, the fluctuations in the changes in the same, as captured by the volatility of the evolution of temperature, are also an important factor driving physical risks, as it is difficult to design mitigation policies in the wake of such uncertainties.

We plot the data for the variables of interest, including GARCH-based natural logarithmic values of volatility of real gold returns used as a control (discussed below), in Figure 1. We report summary statistics of the data in Table 1.

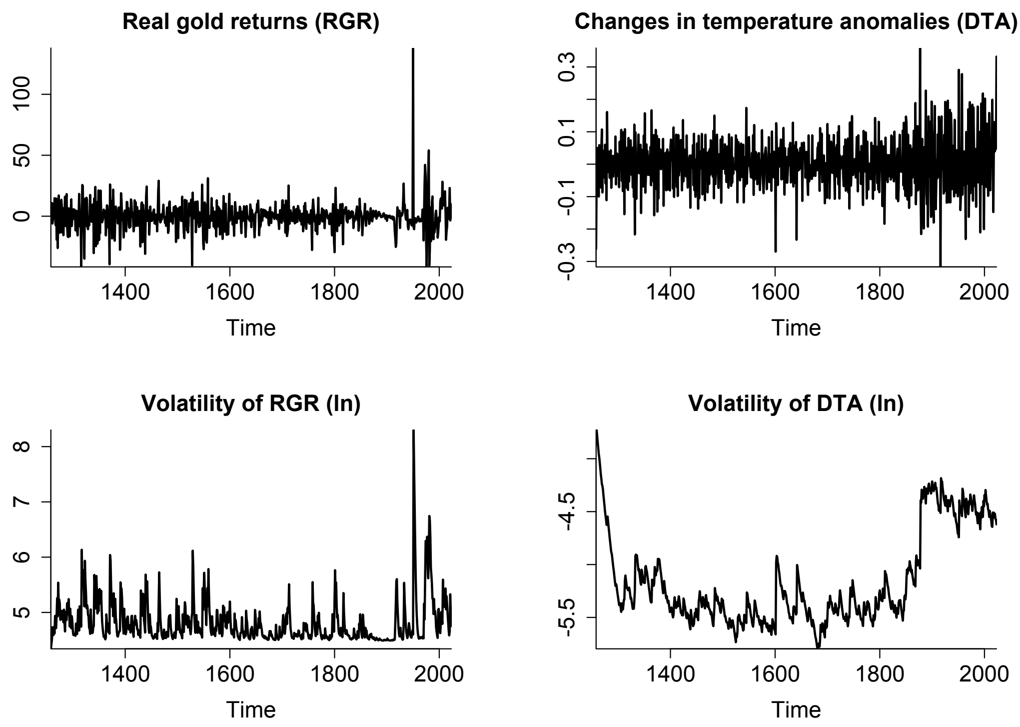


Figure 1. The data.

Table 1. Summary statistics.

Statistic	RGR	DTA	Volatility RGR	Volatility DTA
Mean	−0.2778	0.0020	4.8214	−5.1509
Median	−0.4350	−0.0009	4.6880	−5.3345
Std. Dev.	11.5794	0.0791	0.3889	0.4412
Max	137.9600	0.3583	8.3017	−3.7280
Min	−41.5800	−0.3168	4.3425	−5.7964

RGR = Real gold returns. DTA = Changes in temperature anomalies. Volatility RGR = Volatility of RGR (ln). Volatility DTA = Volatility of DTA (ln).

Using the wavelet localized multiple correlation (WLMC) approach of [53], we found, as we report in Figure A2 at the end of the paper (Appendix A), preliminary evidence, in line with intuition, of a general positive correlation over time, especially at short- and long-horizons. We could confirm this positive association when we linked the conditional quantiles of real gold returns to different quantiles of DTA through a quantile-on-quantile approach [54], in Figure A3.

3. Empirical Models

In order to shed light on the contemporaneous link between real gold returns, RGR, and climate risk, DTA, we considered an autoregressive model with the following format:

$$RGR_t = \beta_0 + \sum_{i=1}^{q} \beta_i RGR_{t-i} + \beta_{q+1} DTA_t + \beta_{q+2} X_t + u_t, \tag{1}$$

where β are the coefficients to be estimated, u_t denotes the usual error term, and q denotes the order of the autoregression coefficients considered, which in our case was found to be equal to 3, as per the Schwarz information criterion (SIC). In addition, X_t captures potential control variables, which in our case were given by a well-established leverage effect (AR-LEV), as outlined in [30], and the volatility of real gold returns (AR-VOLA), with the latter acting as a proxy for general economic uncertainty [55,56], since increases and decreases in gold trading are associated with high and low levels of economic turmoil, due to the safe-haven nature of gold investments, thus increasing or decreasing volatility.

We studied the predictive value of climate risk or subsequent real gold returns by means of the following forecasting regression:

$$RGR_{t+h} = \beta_0 + \sum_{i=1}^{q} \beta_i RGR_{t-i+1} + \beta_{q+1} DTA_t + \beta_{q+2} X_t + u_{t+h}, \tag{2}$$

where $h \geq 1$ denotes the forecast horizon. In our empirical analysis, we mainly focused on the case $h = 1$, because this was the natural forecast horizon in case of our yearly data.

We estimated the regression models specified in Equations (1) and (2) using the ordinary least squares (OLS) technique using a recursive estimation window and a rolling estimation window (specified in more detail in Section 4). We used the R language and environment for statistical computing [57] to estimate our regression models and to conduct our empirical analysis.

It is clear that we could have used much more elaborate linear and nonlinear empirical models for our empirical study than the ones given in Equations (1) and (2). Model complexity, however, is not a value in itself. The OLS models that we used in our empirical research had the advantage that estimation was quite simple, so that we did not have to worry about convergence issues, parameter sensitivity, or the computation time that was needed to estimate the various versions of the models for a recursive and a rolling window and the very long historical sample period that we studied in this research. Moreover, linear prediction models of the type given in Equations (1) and (2) have been extensively studied in much significant earlier research [58] on return predictability in financial markets, given that, in statistical terms, OLS models are robust even if under non-normality of the disturbance terms in (1) and (2).

4. Empirical Results

We summarize our main forecasting results for real gold returns based on Equation (2) in Table 2, where we report the results (p-value, based on robust standard errors) of the Clark–West (CW) test [59] for the comparison of forecasts from two nested models, a benchmark and an extended model, as reported in the first column of the table. The CW test is a one-sided test. Its null hypothesis stipulates an equal predictive performance of the benchmark and the extended models. The alternative hypothesis, in turn, stipulates that the extended model outperforms the benchmark model. We report the test results for a recursive estimation window and a rolling estimation window.

In order to make sure that the GARCH framework that we used to model volatility did not lead to look-ahead bias, we checked that the test results were qualitatively similar when we used the absolute value of RGR and the absolute value of DTA as measures of volatility. The results are not reported, but are available from the authors upon reasonable request.

Table 2. Forecasting results for the linear models.

Benchmark vs. Extended Model	CW Test (p-Value)
	Recursive window
AR vs. AR + DTA	0.0792
AR vs. AR + DTA-VOLA	0.3979
AR vs. AR + DTA + DTA-VOLA	0.0759
AR-LEV vs. AR-LEV + DTA	0.0768
AR-LEV vs. AR-LEV + DTA-VOLA	0.3712
AR-LEV vs. AR-LEV + DTA + DTA-VOLA	0.0692
AR-VOLA vs. AR-VOLA + DTA	0.0601
AR-VOLA vs. AR-VOLA + DTA-VOLA	0.5237
AR-VOLA vs. AR-VOLA + DTA + DTA-VOLA	0.0815
	Rolling window
AR vs. AR + DTA	0.0348
AR vs. AR + DTA-VOLA	0.8397
AR vs. AR + DTA + DTA-VOLA	0.2088
AR-LEV vs. AR-LEV + DTA	0.0113
AR-LEV vs. AR-LEV + DTA-VOLA	0.7715
AR-LEV vs. AR-LEV + DTA + DTA-VOLA	0.0797
AR-VOLA vs. AR-VOLA + DTA	0.0191
AR-VOLA vs. AR-VOLA + DTA-VOLA	0.8243
AR-VOLA vs. AR-VOLA + DTA + DTA-VOLA	0.1730

The table summarizes the results (p-value, based on robust standard errors) of the Clark–West test for a recursive estimation window and a rolling estimation window. The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window was then expanded recursively by one year in every step until the end of the sample period was reached. Similarly, the first rolling estimation window covered the time period until 1376. The rolling estimation window was then expanded by one year in every step, but at the same time one year of data at the very beginning of the rolling estimation window were deleted. The forecast horizon was one year. The benchmark model was an AR(3) (an AR(3)+leverage or an AR(3)+RGR volatility) model, while the alternative model also featured climate risk.

Based on the powerful global L-breaks versus non-multiple structural breaks tests (i.e., $UDmax$ and $WDmax$ statistics of 1 to M globally determined regime changes) of [60] implemented on the benchmark AR(3) model of real gold returns, we chose an initialization period for the recursive estimation window that covered data up to and including 1376, which ensured that the four identified breaks (at: 1377, 1590, 1704, and 1819) fell in the out-of-sample period. We then expanded the estimation window recursively by one year in every step until we reached the end of the sample period. As for the rolling estimation window, we proceeded in a similar way. Our choice for the first rolling estimation window covered the time period until 1376. We expanded the rolling estimation window by one year in every step, but also dropped one year of data at the very beginning of the rolling estimation window, so that the length of the rolling estimation window remained unchanged.

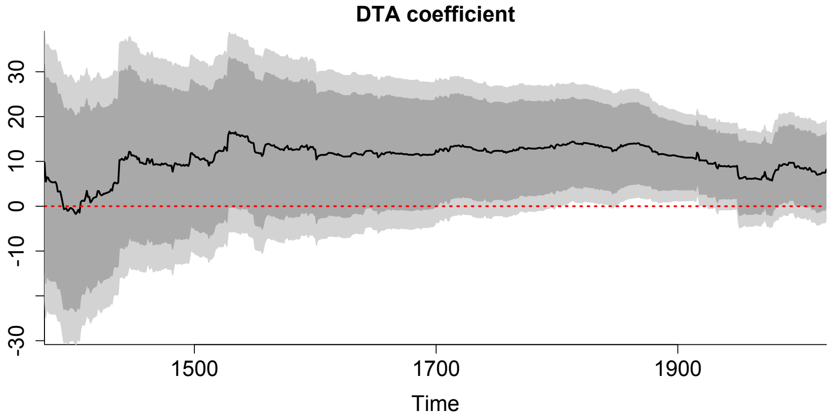
We studied a forecast horizon of one year (the test results for forecast horizons from two to five years turned out to be insignificant and are not reported to save space, but are available from the authors upon reasonable request). While, as stated above, the main baseline benchmark model for real gold returns was an AR(3) model, we also considered benchmark models that featured, in addition, a leverage effect (that is, a predictor that takes on the value of negative returns and the value zero for positive returns) or the (natural logarithm of) volatility of returns. Irrespective of the specific benchmark model that we considered, we found that the alternative model which featured climate risk measured in terms of DTA as a predictor outperformed, as indicated by the significant Clark–West test results, the benchmark model. Furthermore, the models that featured the (natural logarithm of) volatility of DTA as a predictor, in contrast, only yielded significant Clark–West test results when we also considered the DTA, irrespective of whether we used a recursive or a rolling estimation approach. Hence, it was DTA rather than its volatility that contained predictive value for the subsequent real gold returns.

We study the superior performance of the DTA models from a different angle in Figure A1 at the end of the paper (Appendix A), where we plot the ratio of the paths of the ratios of cumulated sums (CUMSUM) of squared forecast errors for two selected benchmarks and DTA models. The paths of the CUMSUM ratios show that the DTA models tended to perform better or equally well compared to the benchmark models during most of our sample period, and only lost ground in the 20th century, a result which is broadly in line with the path of the estimated DTA coefficient in the forecasting model. The result that the DTA models lost ground at the end of the sample period is interesting and deserves to be analyzed in more detail in future research, as it may reflect the influence of several key economic factors. One factor that comes to mind is that significant changes in the larger institutional framework of the gold market took place in the 20th century (e.g., the collapse of the gold standard). Another factor is the substantial degree of financialization that has started to shape commodity market developments in recent years. In this regard, it is important to emphasize that, while we analyzed annual data, important intra-annual climate-related risks (that is, extreme weather events) could have influenced gold returns during a year at higher data frequencies (e.g., at a daily or weekly frequency). Annual data clearly do not suffice to detect such short-term reactions of real gold returns to climate risks, especially in highly financialized commodity markets.

Figures 2 and 3 illustrate graphically the link between real gold returns and DTA, both for a recursive estimation window and a rolling estimation window. Figure 2 sheds light on the contemporaneous link between real gold returns and DTA in terms of the estimated coefficient, β_4, that we obtained from studying a regression model of the format given in Equation (1) with $q = 3$ (along with the corresponding robust confidence intervals). Figure 3, in turn, depicts the predictive value of DTA for real gold returns in terms of the estimated coefficient, β_4, for a regression model of the format in Equation (2) (which we again estimated by setting $q = 3$).

The message to take home from the results for the recursive estimation window that we plot in Panel A of Figure 2 is that the contemporaneous link between real gold returns and DTA was positive and significantly different from zero from approximately the 18th century, where the positive coefficient became smaller and fell somewhat in terms of statistical significance at approximately the mid-20th century. The DTA coefficient estimated based on a rolling estimation window that we plot in Panel B was, as one would have expected, more volatile than the recursively estimated coefficient, but it was also positive, and significantly so between roughly 1700 and 1900. Hence, aggravated climate risk, as measured in terms of a higher realization of DTA, was associated with higher real gold returns during much of our sample period, consistent with the view that investors viewed gold not only as a safe haven in times of (financial) crisis, but also in times of elevated climate risk (or that investors perceived climate risks to be associated with rare disasters and market jitters).

(**A**) Recursive window



(**B**) Rolling window

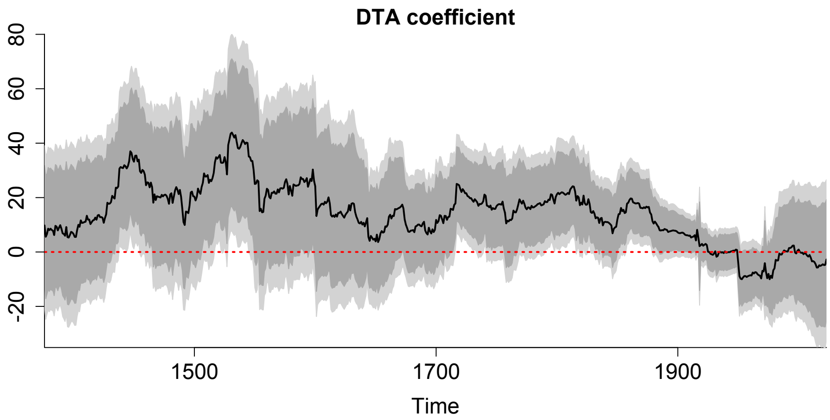
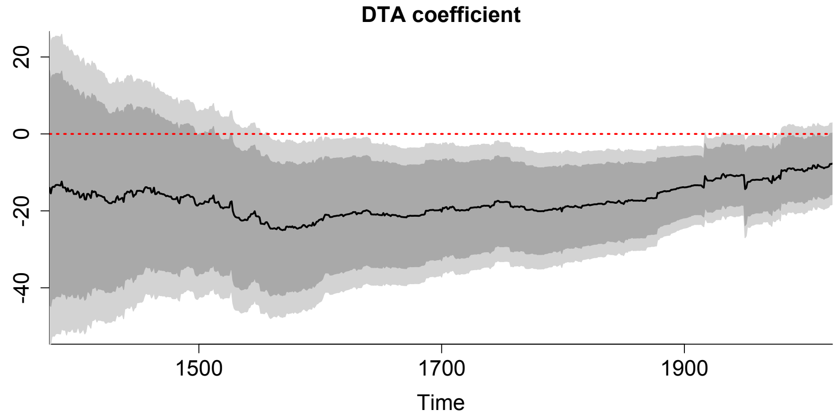


Figure 2. Coefficient of climate risk (contemporaneous link). The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window then expanded recursively by one year in every step until the end of the sample period was reached. Similarly, the first rolling estimation window covered the time period until 1376. The rolling estimation window was then expanded by one year in every step, but, at the same time, one year of data at the very beginning of the rolling estimation window were deleted. The forecast horizon was one year. The results are for an AR(3)+climate risk model: $RGR_t = \beta_0 + \sum_{i=1}^{3} \beta_i RGR_{t-i} + \beta_4 DTA_t + u_t$ The dark-gray area indicates the ± 1.5 standard error band, while the light-gray area indicates the ± 2 standard error band, both computed using robust standard errors.

In contrast to the positive coefficient that we found for the contemporaneous link between real gold returns and DTA, we estimated a negative coefficient when we considered the forecasting regression (Figure 3). When we studied the recursive estimation window (Figure 3A), the coefficient was significantly negative starting from approximately the late 16th century. The coefficient we obtained for a rolling estimation window (Figure 3B) again was more volatile than the coefficient we obtained for the recursive estimation window, but it was, in line with the results for the recursive estimation window, mostly negative during our sample period. Hence, the positive contemporaneous link between real gold returns and DTA was accompanied by a negative forecasting link. While we do not want to stretch the interpretation of these two patterns too far, we observe that this positive-and-then-negative link is consistent with an overshooting scenario in which the real gold price overshot in response to DTA, only to return subsequently to a lower value.

(**A**) Recursive window



(**B**) Rolling window

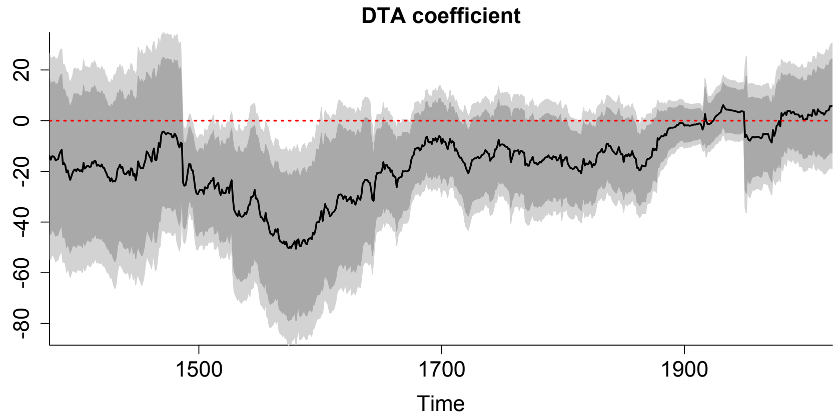
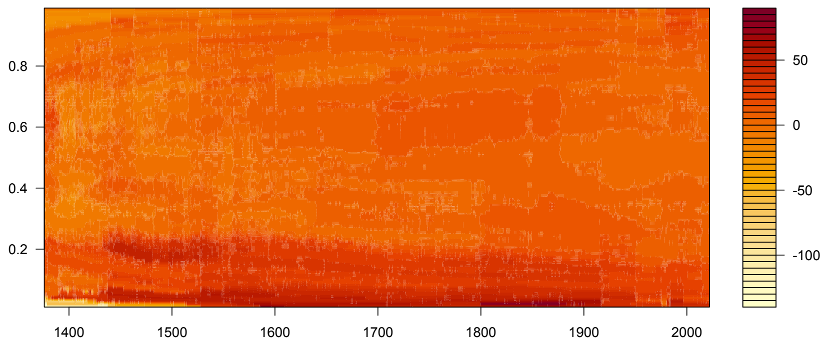


Figure 3. Coefficient of climate risk (forecasting model). The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window then expanded recursively by one year in every step until the end of the sample period was reached. Similarly, the first rolling estimation window covered the time period until 1376. The rolling estimation window was then expanded by one year in every step, but at the same time one year of data at the very beginning of the rolling estimation window were deleted. The forecast horizon was one year. The results are for an AR(3)+climate risk model: $RGR_{t+1} = \beta_0 + \sum_{i=1}^{3} \beta_i RGR_{t-i+1} + \beta_4 DTA_t + u_{t+1}$. The dark-gray area indicates the ± 1.5 standard error band, while the light-gray area indicates the ± 2 standard error band, both computed using robust standard errors.

For completeness, we report in Table A1 (Appendix A) full-sample estimates of the contemporaneous and predictive link of real gold returns with DTA based on an AR(3) + DTA model. In line with the results reported in Figures 2 and 3, the estimated coefficient for the contemporaneous (predictive) link was positive (negative). The estimated coefficient of DTA, however, was not statistically significant for the full-sample estimates, which is not surprising given that the estimates for the full sample of data were not reliable, due to the presence of structural breaks. The full-sample results, thereby, lend further support to our decision to use a recursive estimation window and a rolling estimation window to trace the contemporaneous and predictive link between real gold returns and climate risks.

As an extension and a robustness check, we report in Figure 4 the results of quantile regression models, given the ability of the framework to explain or predict the entire conditional distribution of real gold returns, capturing gold market states and also an element of potential nonlinearity based on quantile-specific coefficients. To this end, we estimated a quantile regression model of real gold returns on a constant, three autoregressive terms, and DTA. We performed estimations using the R add-on package "quantreg" [61]. We estimated this model as a contemporaneous regression model (with period-t real gold returns as the dependent variable), as well as a predictive regression model (with period-$t+1$ real gold returns as the dependent variable), where we focused on the scenario of a recursive estimation window. We then stored the estimated coefficient of DTA for quantiles ranging from 0.01 to 0.99.

(**A**) Contemporaneous link



(**B**) Predictive link

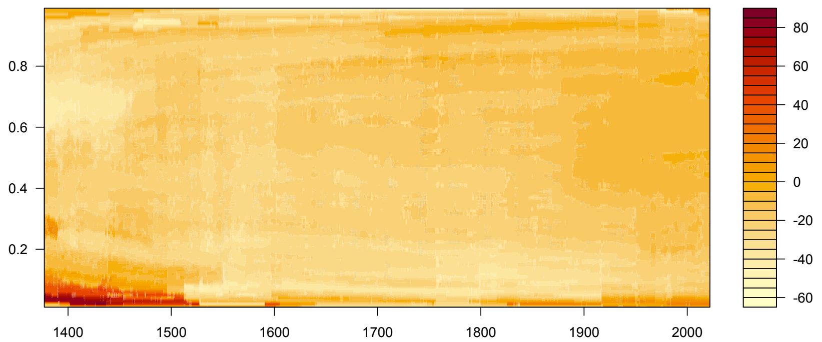


Figure 4. Results for quantile regressions. The figures plot the estimated coefficient of DTA in the contemporaneous quantile regression model $RGR_t = \beta_{0,q} + \sum_{i=1}^{3} \beta_{i,q} RGR_{t-i} + \beta_{4,q} DTA_t + u_t$ (**A**) and the predictive quantile regression model $RGR_{t+1} = \beta_{0,q} + \sum_{i=1}^{3} \beta_{i,q} RGR_{t-i+1} + \beta_{4,q} DTA_t + u_{t+1}$ (**B**). The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window then expanded recursively by one year in every step until the end of the sample period was reached.

We plot the estimated coefficient in Figure 4, where the horizontal axis depicts time and the vertical axis depicts the quantiles. Panel A depicts the estimated coefficient for the contemporaneous regression model, while Panel B depicts the estimated coefficient for the predictive regression model. In line with the results that we report in Figures 2 and 3, we found that the contemporaneous link between the conditional quantiles of real gold returns and DTA was mostly positive across the range of quantiles, but especially for the lower conditional quantiles. The predictive link, in contrast, was mostly negative, except for some years, mainly at the very low end of the range of conditional quantiles.

The results we have presented so far were based on the choice $q = 3$ (selected per the SIC) for the order of the autoregression coefficient. As another robustness check, we checked whether setting $q = 4$, which is the number of lags selected by the Akaike information criterion (AIC) and the Hannan–Quinn criterion (HQC), affected our results. The breaks identified for the case $q = 4$ were the same as those identified for $q = 3$ and, hence, the the out-of-sample period was also the same. Comparing the results for $q = 4$

summarized in Table A2 (Appendix A) with the results reported in Table 2 shows that this change in the the order of the autoregression coefficients gave qualitatively similar results.

Given the fact that the data that we studied extend back to 1258 and, thus, cover an extremely long historical sample period, it is clear that choosing the correct number of breaks is important for obtaining reliable empirical results. We based our choice of the number of breaks, and the specification of the corresponding initialization period, on the results of the 1 to M globally determined multiple structural break tests advocated by [60]. Based on an alternative (but less general) specification of that test, i.e., $L+1$ versus L sequentially determined breaks, we also considered a simple sample split based on only one break, such that the initialization period covered the years up to and including 1594 for the case $q = 3$, and the years up to and including 1589 for the case $q = 4$. In other words, the respective break dates for the AR(3) and AR(4) models were 1595 and 1590. For this alternative setting, we again obtained a combination of a positive contemporaneous and a negative predictive link between real gold returns and DTA, consistent with an overshooting scenario. The results of the CW test, however, turned out to be insignificant, reflecting the fact that extending the initialization period to the late 16th century excluded a substantial proportion of the sample period from the out-of-sample forecasting exercise, during which DTA added a substantial predictive value to the benchmark model (as witnessed by the results plotted in Figure A1), and, thereby, demonstrating that accounting for breaks is of decisive importance. The full set of results for the case of a simple sample split based on only one break are not reported, but are available upon reasonable request from the authors.

5. Concluding Remarks

Using data that cover the annual period from 1258 to 2023, we studied the contemporaneous and the predictive link between real gold returns and climate risks. In doing so, we have contributed to the extensive literature on the safe-haven property of gold investments, as well as to the rapidly growing and significant recent literature on climate risks, rare disasters, and turbulence in financial asset markets. We found a positive contemporaneous link and a negative predictive link, consistent with an overshooting of the real gold price related to climate risks. Importantly, our findings show that the predictive link was historically associated with out-of-sample forecasting gains.

Modeling and forecasting gold returns is of interest to investors for devising hedging strategies, given its role as a safe haven. Naturally, the fact that real gold returns could be historically more accurately forecast one-year-ahead based on climate risks, especially changes in temperature anomalies, over the longest data sample available, thus avoiding any possibility of sample selection bias, should be a valuable finding for investors in making optimal portfolio decisions in the face of accelerating climate change and the increased likelihood of the occurrence of rare disaster events. Moreover, any impact of disaster risks as reflected in changes in temperature anomalies on the subsequent path of real gold returns, a leading indicator [49,50], should carry valuable policy-related information, which opens up the opportunity for central banks and treasuries to respond in a timely fashion to the danger of a recession gathering steam by enhancing the size and persistence of macroeconomic (monetary and fiscal) policies to reduce the likelihood of deep economic crises, and hence hedge climate risks by operating through the gold (and, in general, financial) market.

While using a long span of historical data has its advantages, in our context of climate risks, we only considered here its physical component and not the transition associated with a move to "green technologies" in recent years, with studies like [62,63] highlighting the role played by the latter in gold price movements. Thus, a simultaneous analysis of both physical and transition risks on gold return predictability remains an interesting avenue for future research, even though this would entail covering at most the last two decades or so of data. In addition, contingent on data availability, it would also be interesting to perform an analysis similar to the current one on historical data of other commodities, which, in turn, would allow the comparing and generalization of our current findings, involving the overall commodity sector. Such an extension of our study could also lay the groundwork for research on the impact of climate risks on systemic risk spillover effects among commodity markets, where one could use for such an exploration, for example, the analytical framework studied in recent research by [64].

Another limitation of our research directly follows from the fact that we could only study annual data for the extremely long historical sample period extending back to the 13th century that we studied in our empirical research. As already pointed out above, annual data likely cloud important high-frequency effects of climate risks on real gold returns. Moreover, annual data make it difficult to estimate advanced econometric models that would make it possible to unearth, for example, non-linear effects of climate risks on real gold returns. While the wavelet localized multiple correlation and the quantile regression models that we studied in our research can be interpreted to represent first steps in this direction, a more comprehensive study of such non-linear effects clearly would be an interesting avenue for future research. Non-linear effects could be studied using recent machine learning techniques such as random forests or boosting (see, for example, [65]). Such techniques would also render it possible to account for the potentially confounding effects of macroeconomic variables, as well as important factors such as geopolitical risks and terror attacks [40,66]. At the same time, applying such techniques to higher frequency data, and studying a larger dataset that also contains various macroeconomic, financial, and additional risk factors, would necessarily have the limitation that a researcher would have to focus on a much shorter sample period than the extremely long sample period that we studied in our research.

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Appendix A

(**A**) Recursive window

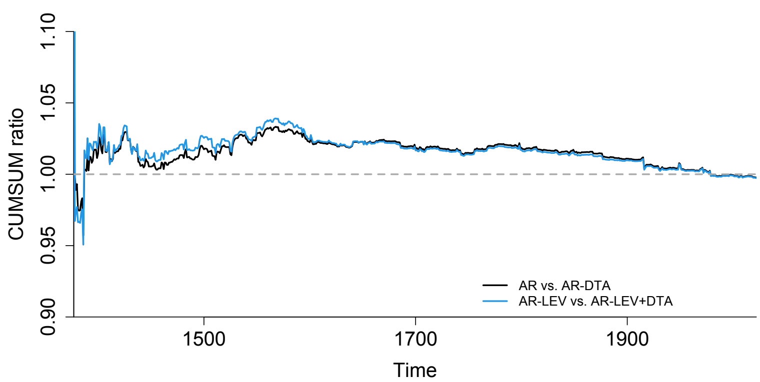

Figure A1. *Cont.*

(**B**) Rolling window

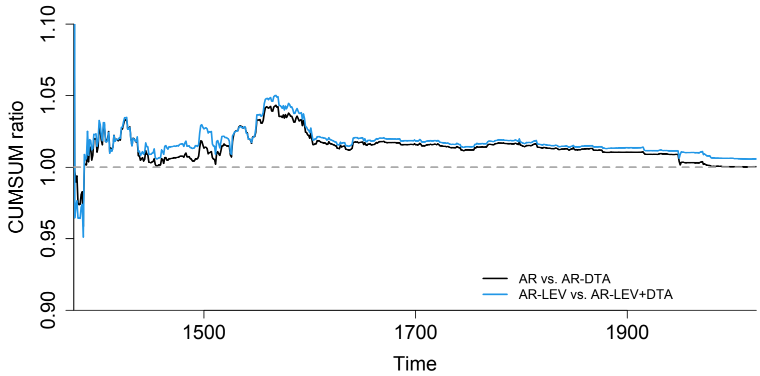

Figure A1. Ratio of the cumulated sum of squared errors. The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window then expanded recursively by one year in every step until the end of the sample period was reached. Similarly, the first rolling estimation window covered the time period until 1376. The rolling estimation window was then expanded by one year in every step, but at the same time one year of data at the very beginning of the rolling estimation window were deleted. The forecast horizon was one year. In a first step, the cumulated sum (CUMSUM) of squared forecast errors was computed for the AR(3) (the AR(3)+leverage) benchmark model and for the alternative AR(3)+DTA (the AR(3)+leverage+DTA)model. In a second step, the ratio of the resulting time series was computed. A CUMSUM ratio larger than unity indicates a superior performance of the alternative model relative to the benchmark model.

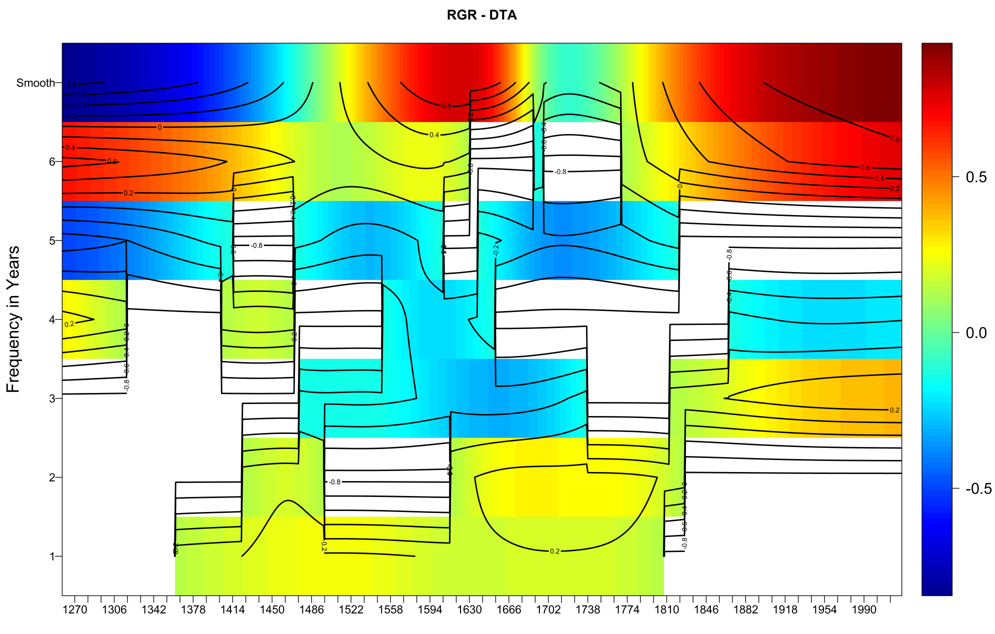

Figure A2. Wavelet localized multiple correlation.

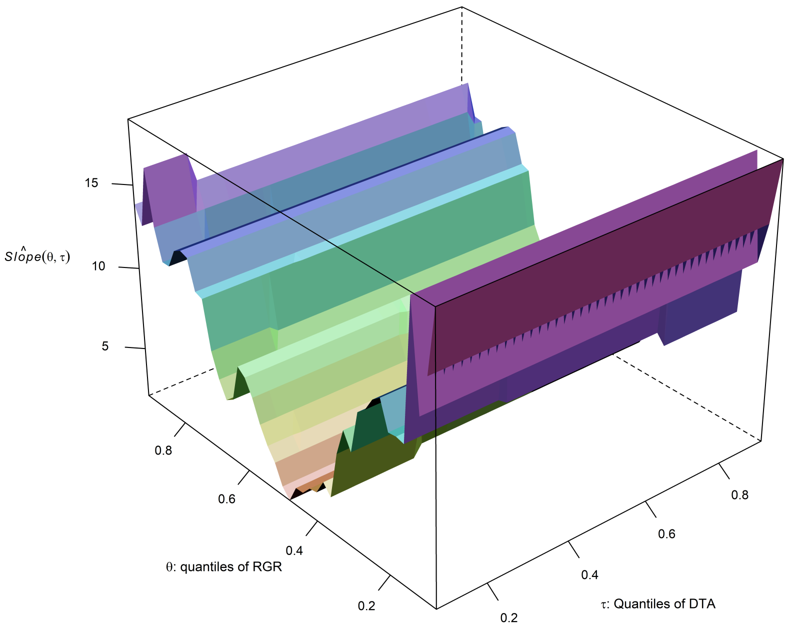

Figure A3. Quantile-on-quantile slope coefficient.

Table A1. Full-sample estimates.

Predictor		Coefficient	t-Statistic
		Contemporaneous link	
Intercept	−0.3925	−0.9662	
RGR_{t-1}	0.0660	1.1538	
RGR_{t-2}	−0.1847	−4.38044	***
RGR_{t-3}	−0.1321	−2.6612	**
DTA_t	8.2055	−1.4854	
		Predictive link	
Intercept	−0.3571	−0.8825	
RGR_t	0.0717	1.3139	
RGR_{t-1}	−0.1854	−4.1257	***
RGR_{t-2}	−0.1316	−2.6200	**
DTA_t	−7.550	−1.4273	

Full-sample results for an AR(3)+climate risk model. RGR = Real gold returns. DTA = Changes in temperature anomalies. The models were estimated by means of the OLS technique using the full sample of data. Contemporaneous link = the dependent variable is RGR_t. Predictive link = the dependent variable is RGR_{t+1}. The t-statistics are based on robust standard errors. **, *** denotes significance at the 5% (1%) level.

Table A2. Forecasting results for AR(4) models.

Benchmark vs. Extended Model	CW Test (*p*-Value)
	Recursive window
AR vs. AR-DTA	0.0992
AR vs. AR-DTA-VOLA	0.3327
AR vs. AR-DTA + DTA-VOLA	0.0855
AR-LEV vs. AR-LEV + DTA	0.0961
AR-LEV vs. AR-LEV + DTA-VOLA	0.3033
AR-LEV vs. AR-LEV + DTA + DTA-VOLA	0.0753
AR-VOLA vs. AR-VOLA + DTA	0.0789
AR-VOLA vs. AR-VOLA + DTA-VOLA	0.4183
AR-VOLA vs. AR-VOLA + DTA + DTA-VOLA	0.0928

Table A2. *Cont.*

Benchmark vs. Extended Model	CW Test (*p*-Value)
	Rolling window
AR vs. AR-DTA	0.0352
AR vs. AR-DTA-VOLA	0.8070
AR vs. AR-DTA + DTA-VOLA	0.2265
AR-LEV vs. AR-LEV + DTA	0.0127
AR-LEV vs. AR-LEV + DTA-VOLA	0.7215
AR-LEV vs. AR-LEV + DTA + DTA-VOLA	0.0976
AR-VOLA vs. AR-VOLA + DTA	0.3929
AR-VOLA vs. AR-VOLA + DTA-VOLA	0.8826
AR-VOLA vs. AR-VOLA + DTA + DTA-VOLA	0.6255

The table summarizes the results (p-value, based on robust standard errors) of the Clark-West test for a recursive estimation window and a rolling estimation window. The initialization period for the recursive estimation window was based on data up to and including 1376. The estimation window then expanded recursively by one year in every step until the end of the sample period was reached. Similarly, the first rolling estimation window covered the time period until 1376. The rolling estimation window was then expanded by one year in every step, but at the same time one year of data at the very beginning of the rolling estimation window were deleted. The forecast horizon was one year. The benchmark model was an AR(4) (an AR(4)+leverage or an AR(4)+RGR volatility) model, while the alternative model featured, in addition, climate risk.

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