Climate Risks and Forecastability of the Realized Volatility of Gold and Other Metal Prices

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Abstract

We 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 (Copper, Palladium, Platinum, Silver). We estimate the HAR-RV models using not only ordinary least squares, but also we use three different popular shrinkage estimators. Our main finding is 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.

JEL classification: C22, C53, Q02

Keywords: Climate Risks; Realized Volatility; Gold; Metals; Forecasting

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1 Introduction

The risks associated with climate change are typically categorized into two groups. The first group comprises physical risks arising due to, for example, rising temperatures, higher sea levels, more destructive storms, and floods or wildfires. The second group comprises the so-called transition risks. Transition risks result from the gradual switchover to a low-carbon economy and include risks due to climate-policy changes, emergence of competitive green technologies, and shifts in consumer preferences.

Understandably, every future scenario includes climate-related financial risks (though the level and form of the underlying uncertainty may vary), and, hence, unsurprisingly climate-related risks have been shown to adversely affect a large number of asset classes including, equities, fixed-income securities, real estate, and even financial institutions (see, Battiston et al., (2021) and Giglio et al., (2021) for detailed reviews of this literature). In other words, climate risks tends to enhance the stress of the entire financial system (Flori et al., 2021).

In the wake of heightened distress in the financial sector due to climate risks, the role of a historically well-established “safe haven" like gold (as shown by Boubaker et al., (2020) based on the entire available history of gold prices available from 1258 until recent years), becomes an important investment vehicle due to its ability to offer portfolio-diversification and/or hedging benefits during periods of financial turmoil. Particularly in such scenarios, accurate forecasts of gold-market volatility contingent on climate risks are pertinent for investors in the pricing of related derivative securities and for devising portfolio-allocation strategies (Asai et al., 2019, 2020).

Against this backdrop, given that rich information contained in intraday data can produce more accurate estimates and forecasts of daily (realized) volatility (McAleer and Medeiros, 2008), we forecast the realized daily volatility (RV) of gold price returns over the period from January, 2000 to November, 2019, as computed from 5-minute-interval data, by employing an augmented version of the popular Heterogeneous Autoregressive (HAR) model introduced by Corsi (2009). More specifically, we extend the classic HAR-RV model to incorporate information on textual-analysis-based daily proxies of physical (natural disasters and global warming) and transition

(U.S. climate policy and international summits) climate risks, recently developed by Faccini et al., (2021).

To the best of our knowledge, this is the first paper that evaluates the out-of-sample forecasting power of climate risks for the RV of gold, and in the process adds to a wide-array of studies that have used the HAR-RV model to forecast the same using variables such as COVID-19 related uncertainty, geopolitical risks, hedging and speculative tendencies of market agents, investor sentiment, risk aversion as predictors (see for example, Demirer et al., (2019), Gkillas et al., (2020), Bonato et al., (2021), Bouri et al., (2021), Luo et al., (forthcoming)). While the focus is on gold, given that recent studies have also depicted the safe-haven characteristic for palladium, platinum, and silver (Lucey and Li, 2015; Salisu et al., 2020), as well as in the case of copper (Lahiani et al., 2021), we also consider the role of climate risks as predictors of the RV of these metals as well. We must point out that, we estimate our HAR-RV models using not only ordinary least squares (OLS), but also we use three different popular shrinkage estimators (the least absolute shrinkage and selection operator (Lasso) estimator, the Ridge-regression estimator, and an elastic net) for the version of the model that includes all climate risk factors.

We organize the remainder of our paper as follows: We describe the data and methodology in Section 2 , summarize our forecasting results in Section 3, and conclude in Section 4.

2 Data and Methodologies

The data on the realized volatility of returns of gold, copper, palladium, platinum, and silver prices are obtained from Risk Lab.[1] Detailed information on how the data are collected and transformed is given on the internet page of Risk Lab, reproduced here for convenience: Risk Lab collects trades at their highest frequencies available, and then cleans them based on the prevalent national best bid and offer that are available, up to every second. The estimation procedure for realized volatility follows Xiu (2010), and uses the quasi-maximum likelihood estimates

[1] Risk Lab is maintained by Professor Dacheng Xiu at Booth School of Business, University of Chicago, with data downloadable from: `https://dachxiu.chicagobooth.edu/#risklab`.

of volatility, building on moving-average models, where non-zero returns of transaction prices are sampled up to their highest frequency available, for days with at least 12 observations. In our research, we use the realized volatility estimates based on 5-minute subsampled returns of the COMEX gold, high-grade copper, and silver futures, and NYMEX palladium and platinum futures, which are the only publicly available robust estimates for realized volatility associated with the metals market.

Based on availability of RVs of the five metals and the climate-risk factors, the data starts for gold, copper, palladium, platinum, and silver at 01/05/2000, 01/05/2000, 01/15/2004, 01/07/2004, and 01/05/2000, and ends at a homogenous date of 11/27/2019. We plot the realized volatilities in Figure 1. We observe that the realized volatilities exhibit the typical large and sudden peaks familiar from the analysis of other financial market data. We also observe that these peaks are scattered throughout the entire sample period in the cases of Gold and Silver, and to a lesser extent in the case of Copper. For Palladium and Platinum, in contrast, the large fluctuations of their realized volatilities are mainly concentrated in the first half of the sample period.

– Figures 1 and 2 about here. –

We plot the autocorrelation functions of the realized volatilities in Figure 2. It is evident that the autocorrelation functions exhibit a characteristic slowly decaying pattern. The HAR-RV model is well-suited to capture such a pattern in the data, and, hence, we use this model as the starting point for our forecasting analysis.

Given the multifaceted nature of climate-change risk, Faccini et al. (2021) employ the Latent Dirichlet Allocation (LDA) technique, an unsupervised textual analysis method, to dissect climate-change risks and construct climate-risk factors. The authors apply LDA to the articles that contain the words “climate change" and “global warming", published over January, 2000 to November, 2019 in Thomson Reuters News Archive. LDA, developed by Blei et al. (2003), deconstructs the news corpus into so-called “topics” that can be characterized in terms of the frequency distribution of its words. Hence, once the LDA technique has identified the topics, Faccini et al., (2021) can give every topic an economic interpretation and, in addition, they can compute time series of the the topic shares (that is, the proportion of an article's text associated with a given topic) that represent how news coverage has evolved over time for any given topic. Finally, Faccini et al., (2021) identify four major climate-related topics of interest: the occurrence of natural disasters, the role of emissions in relation to global warming, U.S. climate policy, and international climate-change summits. The time series of the four climate-related topics are treated as climate-risk factors because their fluctuations signal future effects on the economy.[2] Besides the four continuous climate-risk factors, there is also a fifth factor, which is a dummy variable that Faccini et al., (2021) obtain based on a narrative analysis of U.S. climate policy. Figure 3 plots the five climate-risk factors.

– Figure 3 about here. –

The forecasting models that we use for predicting the realized volatilities are variants of the following model:[3]

$$RV_{t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{t,w} + \beta_3 RV_{t,m} TR_t + \beta_4 x_t + \eta_{t+h}, \tag{1}$$

where $\beta_i, i = 0, ..., 4$ are coefficients to be estimated, and η_{t+h} denotes a disturbance term. The parameter, h, denotes the forecast horizon, where we set $h = 1, 5, 22$ for a daily, weekly, and monthly horizon. For $h > 1$, we forecast the average realized volatility over the relevant forecast horizon. Moreover, $RV_{t,w}$ denotes the average weekly realized volatility from day $t-5$ to month $t-1$, and $RV_{t,m}$ denotes the average monthly realized volatility from day $t-22$ to month $t-1$.

The benchmark HAR-RV model obtains upon setting $\beta_4 = 0$, such that any additional predictor, x_t is not included in the forecasting model. Extended versions of the HAR-RV model, in turn, obtain upon setting x_t to one of the climate-risk factors. We also consider an extended HAR-RV

[2]The data is freely available for download from the website of Dr. Renato Faccini at: `https://sites.google.com/site/econrenatofaccini/home/research?authuser=0`.

[3]The key feature of the HAR-RV model is that it uses volatilities from different time resolutions to forecast the realized volatility of metal-price returns. The model, thereby, captures the main idea motivating the so-called heterogeneous market hypothesis (Müller et al., 1997). Despite its apparently simple structure, the HAR-RV model can capture various volatility properties of metals (i.e., long memory (Gil-Alana et al., 2015) and multi-scaling behavior (Wang et al., 2019)).

model that includes all five different climate-risk factors, in which case x_t denotes a vector of predictors and β_4 denotes an appropriately dimensioned vector of coefficients to be estimated.

Given that Figure 1 clearly demonstrates the changing dynamics of the realized volatilities, we use a rolling-estimation window of length one year (that is, the window comprises 250 observations) to estimate the models given in Equation (1) and to compute forecasts of the realized volatilities, where we construct the data matrix in such a way so that the data matrix has the same dimension for all forecast horizons.

In our baseline scenario, we estimate the forecasting models given in Equation 1 by the OLS technique. In an extended scenario, we use three different popular shrinkage estimators of the version of the model that includes all five climate-risk factors as extra predictors. We consider three shrinkage estimators: the Lasso estimator, the Ridge-regression estimator, and an elastic net. The Lasso estimator uses the L1 norm of the coefficient vector to shrink the dimension of the estimated forecasting model, the Ridge-regression estimator uses the L2 norm, and our elastic net uses an equally weighted combination of the two norms. We use 10-fold cross-validation to determine the optimal shrinkage parameter which, in our cases, minimizes the mean cross-validated error.[4]

3 Empirical Results

Before proceeding with our ouf-of-sample forecasting analysis, we lay out in Table 1 full-sample estimation results. The results demonstrate that, as expected, the estimated coefficients of the HAR-RV model are highly significant and positive for all metals. In sharp contrast, the estimated coefficients of the climate-risk factors are mostly insignificant with only a few exceptions like, for example, international summits in the case of gold, copper, and silver for the monthly forecast horizon. Moreover, the evidence is mixed with regard to the sign of the the estimated coefficients.

[4]We use the R language and environment for statistical computing (R Core Team, 2019) to set up our forecasting experiment. We use the R add-on package "glmnet" (Friedman et al., 2010) to estimate the Lasso model, where we use 10-fold cross-validation to select the shrinkage parameter that minimizes the mean cross-validated error.

While the majority of estimated coefficients have a positive sign, other estimated coefficients have a negative sign, where we also observe a switching sign across forecast horizons in some cases.[5] Finally, the (adjusted) coefficient of determination increases when we move from the daily to the weekly forecast horizon, and then stays more or less constant or even decreases somewhat when we move on to the long forecast horizon. Taken together, the full-sample results are difficult to interpret in economic terms, and there is no clear-cut conclusion as to whether and how the climate-risk factors help to predict subsequent the realized volatility. We, therefore, turn next to our out-of-sample analysis, which, as Campbell (2008) points out, is the ultimate test of any predictive model in terms of the econometric methodology and the predictor(s) employed.

– Tables 1 and 2 about here. –

We summarize our baseline out-of-sample forecasting results in Table 2, where we report the p-values of the test advocated by Clark and West (2007) . In stark contrast to the largely insignificant full-sample results, we observe that the majority of tests yields significant results for the monthly forecast horizon. The test results for the daily forecast horizon are insignificant (with only one exception), as are those for the weekly forecast horizon, where some test results are significant in the case of Copper and especially Platinum. Interestingly, four out of the five tests for the model that includes US climate policy as a predictor are significant when we study the weekly forecast horizon. The key message to take home from the test results, however, is that climate-risk factors help to improve the accuracy of forecasts of realized volatility, and they do so in the majority of cases at the monthly forecast horizon.

As a robustness check, we report in Table 3 test results for the square root of RV. The motivation for undertaking such a robustness check stems from the observation (see Figure 1) that the

[5] An increase in the value of the climate-risk factor may signal a positive or a negative future effect to the economy. Faccini et al. (2021) argue that an increase in the natural disasters and global warming (via increased media coverage of sources of concern) and international summits factors (because policymakers often use such summits as platforms to discuss issues related to a global tax on pollutants) is likely to signal "bad news" for the economy. An increase in the coverage of the U.S. climate policy news, in turn, may signal an increase or decrease in transition risks depending on which political party holds the political power. Hence, the mixed-sign is not surprising. The dominant number of positive sign though is in line with our expectation that, in the wake of "bad news", volatility of safe-haven assets will increase due to higher returns emanating from higher demand and hence increased trading (Baur, 2012).

realized volatility historically exhibited occasional large peaks. The key result of this robustness check is that the test results for the square-root model corroborate the results we report in Table 2 in that we observe significant test results mainly in the case of the monthly forecast horizon. Platinum is an exception insofar as the test results for this precious metal are significant also for the weekly forecast horizon. Again, US climate policy helps to improve forecast accuracy at the weekly forecast horizon in four out of five cases.

– Tables 3 and 4 about here. –

As a modification of our baseline forecasting scenario, we next present the results we obtain when we use well-known shrinkage estimators to estimate the HAR-RV cum all climate-risk factors model. The advantage of the shrinkage estimators is that they select a parsimonious forecasting model in a fully data-driven way. In Table 4, we report the results for the three shrinkage estimators that we consider in this research: the Lasso estimator, the Ridge-regression estimator, and an elastic net, which balances the Lasso and Ridge-regression estimator. The message to take home is that the forecasts that we compute by means of the shrinkage estimators estimators are superior to the forecasts we obtain from the benchmark HAR-RV model (estimated by ordinary-least squares) in case of the monthly forecast horizon. For Platinum the test results are also significant at the weekly forecast horizon.

– Table 5 about here. –

As a further extension of our empirical analysis, we conduct a bootstrap analysis. To this end, we sample without replacement 0.632 precent of the data. We then estimate the forecasting models on the sampled data. Next, we combine the estimated forecasting models with the the hold-out data (also known as the out-of-bag data in the statistical-learning) to out-of-bag forecasts of the realized variance. We repeat this process 10,000 times. Finally, we compute forecasts for the entire data set by averaging across the out-of-bag forecasts and use the Clark-West test to study the contribution of the climate-risk factors to forecast accuracy. Table 5 summarizes the test results. We observe significant test results for Gold (all tests yield significant results), Copper (only the test for natural disasters is not significant), and Silver (the results for the global warming and narrative factor are insignificant) in case of the monthly forecast horizon. We also observe some significant test results for these three metals when we consider a weekly forecast horizon, mainly for Gold and Copper. Forecasts of the realized variance of gold-price movements also benefit in the case of the daily forecast horizon when US climate policy, international summits, or global warming are added as a predictor to the forecasting model. The test results for Palladium and Platinum are insignificant, which is not surprising because Figure 1 shows that these two metals differ from the other three metals in our sample in that the large peaks of the realized volatilities are mainly concentrated in the first half of the sample period. Hence, estimating the forecasting models on data randomly selected from the entire sample period is likely to produce out-of-bag forecasts that are less informative than the forecasts computed by means of a rolling-estimation window. Taken together, however, we again obtain evidence demonstrating that considering the climate-risk factors as predictors improves forecast accuracy at the monthly forecast horizon rather than at the two shorter forecast horizons.

4 Concluding Remarks

The role of gold as a traditional safe-haven during periods of heightened financial stress is well-established in the empirical-finance literature as well as in the financial media. Given the recent evidence that climate risks tend to drive financial distress, we extend the literature to a novel direction by exploring the predictive power of risks related to climate change for the realized volatility of gold returns as derived from intraday data. Utilizing recently proposed textual analysis-based daily proxies of physical and transition climate risks, we focus on the out-of-sample forecasting performance of various HAR-RV models by incorporating these risks as possible predictors. We also conduct similar analyses for other metals like copper, palladium, platinum and silver.

We find that, while in-sample results are largely insignificant, the five climate-risk factors that we have studied in our empirical research tend to improve the accuracy of out-of-sample forecasts of realized volatility of the returns of gold, copper, palladium, platinum and silver prices at a monthly and, in some cases, also at a weekly forecast horizon.

Given the importance of accurate volatility forecasts for the pricing of derivatives as well as the computation of optimal investment positions, our findings suggest that incorporating climate risks in forecasting models can help to improve the design of portfolios that include gold and other precious metals as a hedge against financial market risks primarily at a longer (month-ahead) forecast horizon. As part of future research, an interesting exercise is to conduct a similar analysis for the energy market.

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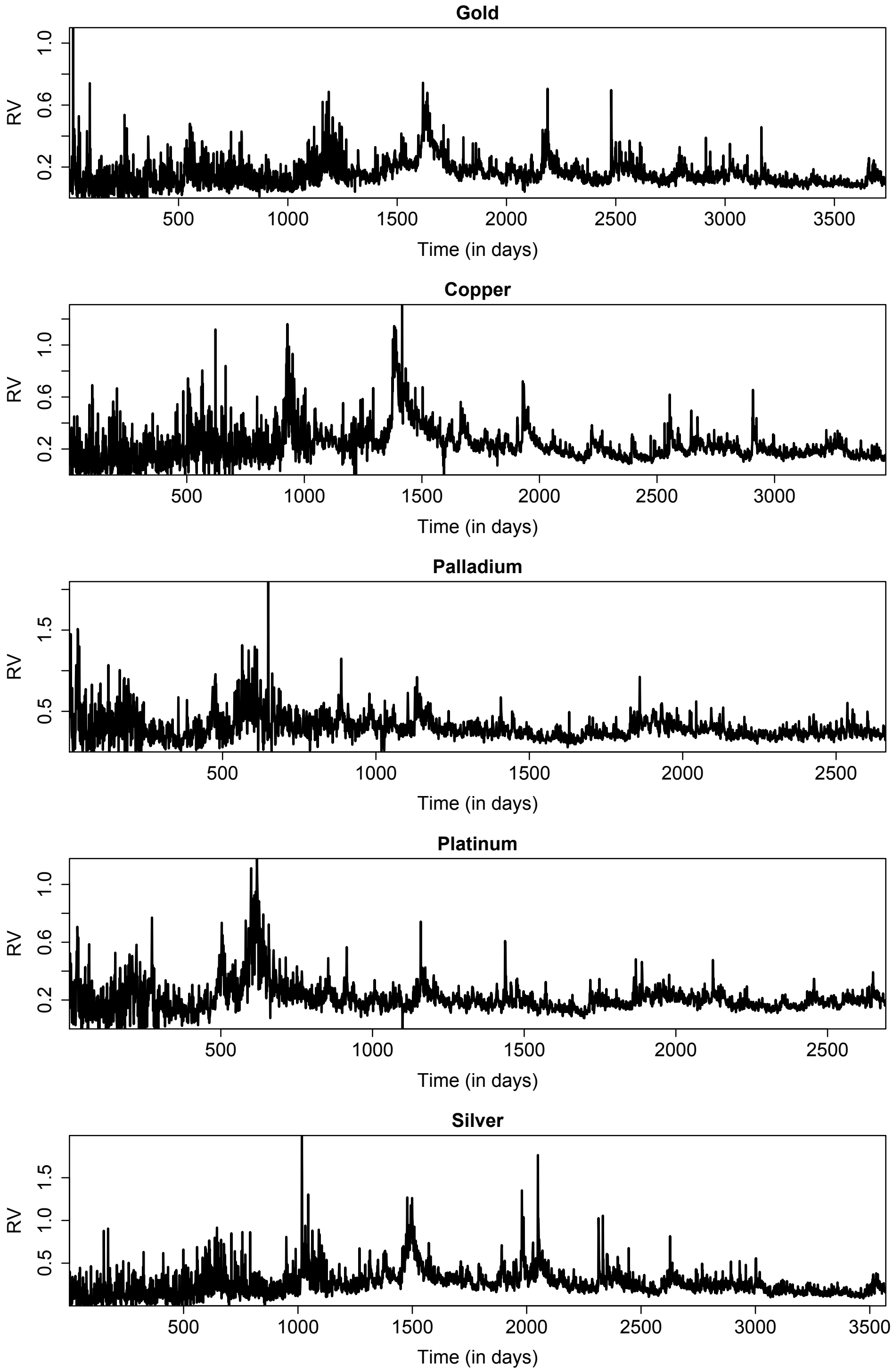
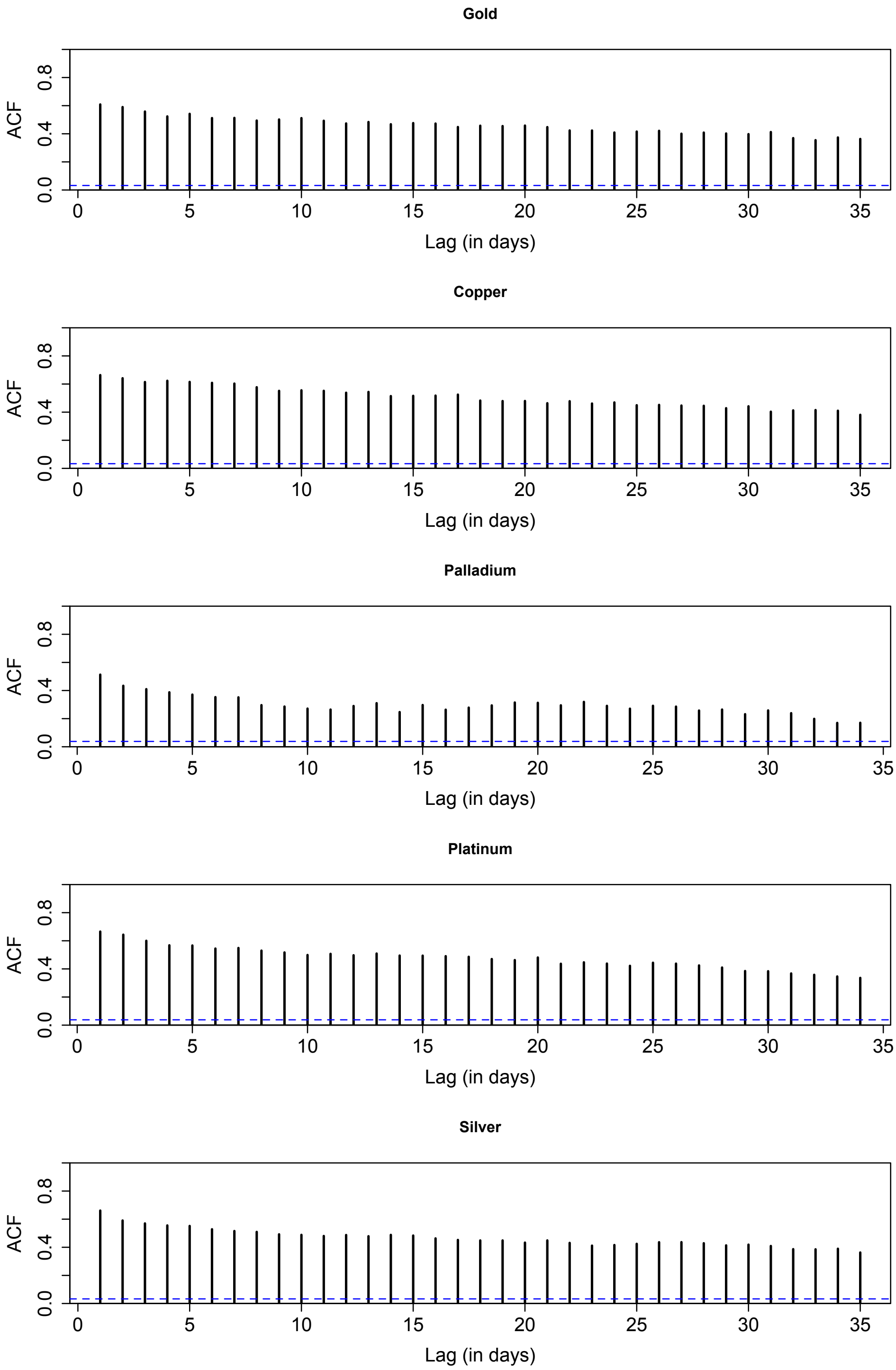
Figure 1: Realized Volatilities



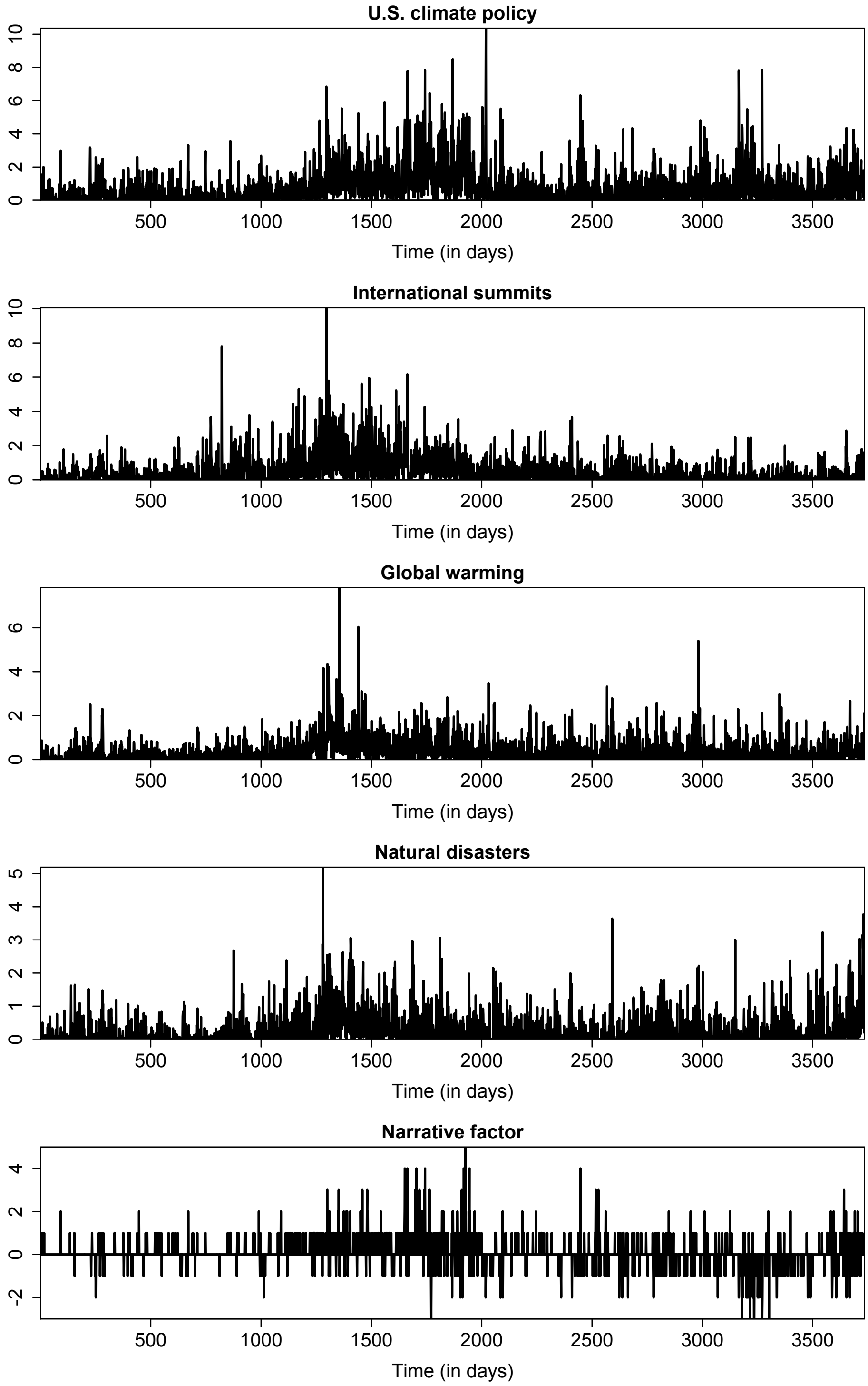
RV denotes the realized variance of the returns of the prices of the respective metals. The sample periods depend upon data availability and are given as follows: Gold: 01/05/2000−11/27/2019, Copper: 01/05/2000−11/27/2019, Palladium: 01/15/2004−11/27/2019, Palladium: 01/07/2004−11/27/2019, Silver: 01/05/2000−11/27/2019

Figure 2: Autocorrelation Functions



ACF denotes the autocorrelation function of the realized volatility of the returns of the prices of the respective metals. The dashed horizontal line denotes the 95% confidence line. The sample periods depend upon data availability and are given as follows: Gold: 01/05/2000−11/27/2019, Copper: 01/05/2000−11/27/2019, Palladium: 01/15/2004−11/27/2019, Palladium: 01/07/2004−11/27/2019, Silver: 01/05/2000−11/27/2019

Figure 3: Climate Risks



The sample period depends on the metal being studied. In this figure, the sample period is the one for gold: 01/05/2000−11/27/2019.

Table 1: Full-Sample Results

Metal	h=1	h=1	h=5	h=5	h=22	h=22
Gold						
Predictor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.0102	0.0011	0.0146	0.0289	0.0281	0.0082
RV	0.2655	0.0000	0.2037	0.0000	0.1621	0.0000
RV (weekly)	0.3045	0.0000	0.2821	0.0000	0.3163	0.0021
RV (monthly)	0.3425	0.0000	0.4045	0.0000	0.3229	0.0000
U.S. climate policy	0.0021	0.0667	0.0013	0.1589	0.0004	0.6771
International summits	0.0015	0.2603	0.0011	0.3159	0.0032	0.0130
Global warming	0.0027	0.1245	0.0024	0.0631	0.0004	0.8094
Natural disasters	-0.0011	0.5504	-0.0005	0.7494	0.0031	0.2497
Narrative factor	0.0008	0.6005	0.0011	0.3562	0.0012	0.2365
Adjusted R2	0.5220	–	0.7049	–	0.7029	–
Copper						
Predictor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.0150	0.0011	0.0234	0.0019	0.0482	0.0000
RV	0.2473	0.0000	0.2117	0.0000	0.1751	0.0000
RV (weekly)	0.4888	0.0000	0.4873	0.0000	0.3695	0.0008
RV (monthly)	0.1813	0.0017	0.1847	0.0667	0.2228	0.0595
U.S. climate policy	0.0024	0.1239	0.0022	0.2010	0.0019	0.2577
International summits	0.0011	0.7014	0.0047	0.0954	0.0103	0.0257
Global warming	0.0035	0.2190	0.0008	0.7026	-0.0008	0.7325
Natural disasters	0.0020	0.5875	-0.0024	0.3414	0.0003	0.9443
Narrative factor	0.0008	0.6886	0.0013	0.4652	0.0037	0.0510
Adjusted R2	0.5744	–	0.7491	–	0.6865	–
Palladium						
Predictor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.0354	0.0006	0.0422	0.0107	0.0751	0.0001
RV	0.2988	0.0000	0.1762	0.0000	0.1195	0.0000
RV (weekly)	0.2625	0.0001	0.1682	0.0581	0.1950	0.0170
RV (monthly)	0.3165	0.0000	0.5038	0.0000	0.4277	0.0001
U.S. climate policy	0.0018	0.5022	0.0018	0.4676	0.0015	0.4734
International summits	-0.0014	0.7622	-0.0010	0.7977	0.0030	0.3927
Global warming	0.0055	0.2402	0.0036	0.2528	-0.0043	0.0855
Natural disasters	-0.0080	0.0763	0.0014	0.7389	0.0036	0.3962
Narrative factor	-0.0012	0.7975	-0.0032	0.3255	-0.0008	0.7488
Adjusted R2	0.3651	–	0.5355	–	0.5807	–
Platinum						
Predictor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.0131	0.067	0.0218	0.0700	0.0436	0.0194
RV	0.3244	0.0000	0.2401	0.0000	0.1948	0.0000
RV (weekly)	0.3337	0.0000	0.3216	0.0000	0.3513	0.0118
RV (monthly)	0.2617	0.0000	0.3300	0.0000	0.2398	0.0255
U.S. climate policy	0.0024	0.0970	0.0009	0.5168	0.0001	0.9430
International summits	0.0016	0.5109	0.0027	0.2640	0.0033	0.2680
Global warming	0.0047	0.0654	0.0010	0.5840	-0.0007	0.7005
Natural disasters	-0.0031	0.4331	-0.0042	0.2426	0.0018	0.7435
Narrative factor	-0.0012	0.5202	-0.0012	0.4354	-0.0001	0.9179
Adjusted R2	0.5552	–	0.7095	–	0.6752	–
Silver						
Predictor	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
Intercept	0.0204	0.0000	0.0297	0.0057	0.0521	0.0066
RV	0.3484	0.0000	0.2349	0.0000	0.1571	0.0000
RV (weekly)	0.2937	0.0000	0.2759	0.0000	0.2120	0.0085
RV (monthly)	0.2704	0.0000	0.3674	0.0000	0.4210	0.0000
U.S. climate policy	0.0017	0.3153	0.0010	0.6139	0.0011	0.5476
International summits	0.0033	0.2379	0.0032	0.1592	0.0060	0.0263
Global warming	0.0033	0.2610	0.0023	0.3578	-0.0025	0.4265
Natural disasters	-0.0054	0.1097	-0.0012	0.7065	0.0054	0.2376
Narrative factor	0.0031	0.2579	0.0010	0.6269	0.0009	0.6616
Adjusted R2	0.5329	–	0.6736	–	0.6691	–

The p-values are based on robust heteroskedasticity and autocorrelation consistent standard errors. The parameter *h* denotes the forecast horizon (in days).

Table 2: Baseline Test Results

Metal / Model	h=1	h=5	h=22
Gold			
HAR-RV vs. U.S. climate policy	0.6153	0.2026	0.0001
HAR-RV vs. International summits	0.2139	0.2881	0.1555
HAR-RV vs. Global warming	0.2226	0.1929	0.0031
HAR-RV vs. Natural disasters	0.6606	0.2868	0.0572
HAR-RV vs. Narrative factor	0.8047	0.7658	0.1073
HAR-RV vs. All	0.4594	0.2493	0.0001
Copper			
HAR-RV vs. U.S. climate policy	0.7333	0.0806	0.0003
HAR-RV vs. International summits	0.9213	0.2026	0.0056
HAR-RV vs. Global warming	0.0311	0.1358	0.0184
HAR-RV vs. Natural disasters	0.4631	0.2229	0.0521
HAR-RV vs. Narrative factor	0.6995	0.1952	0.3531
HAR-RV vs. All	0.4813	0.0217	0.0000
Palladium			
HAR-RV vs. U.S. climate policy	0.4968	0.0462	0.0000
HAR-RV vs. International summits	0.8498	0.5172	0.4744
HAR-RV vs. Global warming	0.1919	0.8713	0.0043
HAR-RV vs. Natural disasters	0.5442	0.5043	0.5475
HAR-RV vs. Narrative factor	0.9205	0.1020	0.0051
HAR-RV vs. All	0.8007	0.1604	0.0001
Platinum			
HAR-RV vs. U.S. climate policy	0.6061	0.0038	0.0001
HAR-RV vs. International summits	0.8874	0.8095	0.5862
HAR-RV vs. Global warming	0.8919	0.4812	0.0094
HAR-RV vs. Natural disasters	0.6705	0.0628	0.1086
HAR-RV vs. Narrative factor	0.9974	0.0575	0.0548
HAR-RV vs. All	0.9134	0.0016	0.0000
Silver			
HAR-RV vs. U.S. climate policy	0.9776	0.0224	0.0000
HAR-RV vs. International summits	0.8241	0.5621	0.2055
HAR-RV vs. Global warming	0.7265	0.2246	0.0047
HAR-RV vs. Natural disasters	0.6127	0.2183	0.5808
HAR-RV vs. Narrative factor	0.2598	0.1951	0.0299
HAR-RV vs. All	0.8384	0.1628	0.0000

Results (p-values; robust heteroskedasticity and autocorrelation consistent standard errors) of the Clark-West tests for an equal mean-squared prediction error are based on robust standard errors. The classic HAR-RV model is the benchmark model , and the model extended to include climate-risk factors is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The parameter h denotes the forecast horizon (in days). The models are estimated using a rolling-estimation window of length 250 observations.

Table 3: Test Results for $\sqrt{RV}$

Metal / Model	h=1	h=5	h=22
Gold			
HAR-RV vs. U.S. climate policy	0.6216	0.2810	0.0004
HAR-RV vs. International summits	0.1673	0.2829	0.1283
HAR-RV vs. Global warming	0.2759	0.3125	0.0085
HAR-RV vs. Natural disasters	0.4003	0.5217	0.1019
HAR-RV vs. Narrative factor	0.8087	0.6829	0.0842
HAR-RV vs. All	0.3899	0.3748	0.0004
Copper			
HAR-RV vs. U.S. climate policy	0.4257	0.0737	0.0002
HAR-RV vs. International summits	0.9575	0.3402	0.0034
HAR-RV vs. Global warming	0.0211	0.1132	0.0290
HAR-RV vs. Natural disasters	0.3914	0.2751	0.0379
HAR-RV vs. Narrative factor	0.6446	0.3293	0.3653
HAR-RV vs. All	0.3857	0.0631	0.0000
Palladium			
HAR-RV vs. U.S. climate policy	0.6560	0.0446	0.0000
HAR-RV vs. International summits	0.7841	0.1545	0.2934
HAR-RV vs. Global warming	0.2835	0.8770	0.0026
HAR-RV vs. Natural disasters	0.6825	0.5337	0.5000
HAR-RV vs. Narrative factor	0.9246	0.1138	0.0031
HAR-RV vs. All	0.8973	0.1821	0.0000
Platinum			
HAR-RV vs. U.S. climate policy	0.5946	0.0067	0.0001
HAR-RV vs. International summits	0.5794	0.6951	0.5192
HAR-RV vs. Global warming	0.8549	0.7308	0.0137
HAR-RV vs. Natural disasters	0.7209	0.0401	0.0488
HAR-RV vs. Narrative factor	0.9925	0.0583	0.0458
HAR-RV vs. All	0.8449	0.0036	0.0000
Silver			
HAR-RV vs. U.S. climate policy	0.9861	0.0799	0.0000
HAR-RV vs. International summits	0.6707	0.2239	0.1157
HAR-RV vs. Global warming	0.7781	0.3159	0.0114
HAR-RV vs. Natural disasters	0.6754	0.5643	0.7419
HAR-RV vs. Narrative factor	0.3628	0.3046	0.0199
HAR-RV vs. All	0.8806	0.2830	0.0000

Results (p-values; robust heteroskedasticity and autocorrelation consistent standard errors) of the Clark-West tests for an equal mean-squared prediction error are based on robust standard errors. The classic HAR-RV model is the benchmark model , and the model extended to include climate-risk factors is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The parameter h denotes the forecast horizon (in days). The models are estimated using a rolling-estimation window of length 250 observations.

Table 4: Shrinkage Results

Metal / Model	h=1	h=5	h=22
Gold			
HAR-RV vs. Lasso	0.8212	0.4458	0.0041
HAR-RV vs. Ridge	0.1582	0.0932	0.0014
HAR-RV vs. Elastic net	0.5820	0.5275	0.0039
Copper			
HAR-RV vs. Lasso	0.2413	0.1402	0.0060
HAR-RV vs. Ridge	0.2207	0.0731	0.0039
HAR-RV vs. Elastic net	0.2408	0.2207	0.0156
Palladium			
HAR-RV vs. Lasso	0.7928	0.1361	0.0002
HAR-RV vs. Ridge	0.7325	0.1622	0.0008
HAR-RV vs. Elastic net	0.6966	0.1917	0.0001
Platinum			
HAR-RV vs. Lasso	0.9072	0.0695	0.0030
HAR-RV vs. Ridge	0.6530	0.0084	0.0328
HAR-RV vs. Elastic net	0.7010	0.0685	0.0140
Silver			
HAR-RV vs. Lasso	0.7327	0.4558	0.0029
HAR-RV vs. Ridge	0.3496	0.1651	0.0047
HAR-RV vs. Elastic net	0.6078	0.3858	0.0065

Results (p-values; robust heteroskedasticity and autocorrelation consistent standard errors) of the Clark-West tests for an equal mean-squared prediction error are based on robust standard errors. The classic HAR-RV model is the benchmark model, and the model extended to include all climate-risk factors and estimated by the Lasso, Ridge, and elastic-net estimator is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The parameter h denotes the forecast horizon (in days). The models are estimated using a rolling-estimation window of length 250 observations.

Table 5: Bootstrap Results

Metal / Model	h=1	h=5	h=22
Gold			
HAR-RV vs. U.S. climate policy	0.0077	0.0214	0.0489
HAR-RV vs. International summits	0.0498	0.0553	0.0005
HAR-RV vs. Global warming	0.0153	0.0057	0.0231
HAR-RV vs. Natural disasters	0.7462	0.4775	0.0308
HAR-RV vs. Narrative factor	0.3896	0.1832	0.0510
HAR-RV vs. All	0.0076	0.0108	0.0002
Copper			
HAR-RV vs. U.S. climate policy	0.0478	0.0495	0.0082
HAR-RV vs. International summits	0.4640	0.0127	0.0000
HAR-RV vs. Global warming	0.0347	0.1544	0.0576
HAR-RV vs. Natural disasters	0.3051	1.0000	0.2312
HAR-RV vs. Narrative factor	0.6116	0.2290	0.0028
HAR-RV vs. All	0.1861	0.0098	0.0000
Palladium			
HAR-RV vs. U.S. climate policy	0.8583	0.4646	0.3375
HAR-RV vs. International summits	0.9998	1.0000	0.2805
HAR-RV vs. Global warming	0.5626	0.1798	0.6188
HAR-RV vs. Natural disasters	0.2769	0.6241	0.3529
HAR-RV vs. Narrative factor	0.9839	0.5533	1.0000
HAR-RV vs. All	0.9048	0.6443	0.2450
Platinum			
HAR-RV vs. U.S. climate policy	0.0579	0.3821	0.5748
HAR-RV vs. International summits	0.3120	0.2135	0.1311
HAR-RV vs. Global warming	0.0414	0.6224	0.7054
HAR-RV vs. Natural disasters	0.9998	0.4033	0.5376
HAR-RV vs. Narrative factor	1.0000	0.9360	0.9828
HAR-RV vs. All	0.1405	0.2204	0.3474
Silver			
HAR-RV vs. U.S. climate policy	0.1378	0.2467	0.0999
HAR-RV vs. International summits	0.1397	0.0724	0.0045
HAR-RV vs. Global warming	0.2017	0.1247	0.5010
HAR-RV vs. Natural disasters	0.7349	0.9507	0.0749
HAR-RV vs. Narrative factor	0.2114	0.5227	0.3301
HAR-RV vs. All	0.1173	0.1896	0.0038

Results (p-values; robust heteroskedasticity and autocorrelation consistent standard errors) of the Clark-West tests for an equal mean-squared prediction error are based on robust standard errors. The classic HAR-RV model is the benchmark model, and the model extended to include all climate-risk factors and estimated by the Lasso, Ridge, and elastic-net estimator is the rival model. The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. The parameter *h* denotes the forecast horizon (in days).