Article

Climate Risks and Stock Market Volatility over a Century in an Emerging Market Economy: The Case of South Africa

Kejin Wu [1,*], Sayar Karmakar [2], Rangan Gupta [3] and Christian Pierdzioch [4]

1   Department of Mathematics, University of California San Diego, La Jolla, CA 92093, USA
2   Department of Statistics, University of Florida, Gainesville, FL 32611, USA; sayarkarmakar@ufl.edu
3   Department of Economics, University of Pretoria, Pretoria 0002, South Africa; rangan.gupta@up.ac.za
4   Department of Economics, Helmut Schmidt University, 22043 Hamburg, Germany
*   Correspondence: kwu@ucsd.edu

Abstract: Because climate change broadcasts a large aggregate risk to the overall macroeconomy and the global financial system, we investigate how a temperature anomaly and/or its volatility affect the accuracy of forecasts of stock return volatility. To this end, we do not apply only the classical GARCH and GARCHX models, but rather we apply newly proposed model-free prediction methods, and use GARCH-NoVaS and GARCHX-NoVaS models to compute volatility predictions. These two models are based on a normalizing and variance-stabilizing transformation (NoVaS transformation) and are guided by a so-called model-free prediction principle. Applying the new models to data for South Africa, we find that climate-related information is helpful in forecasting stock return volatility. Moreover, the novel model-free prediction method can incorporate such exogenous information better than the classical GARCH approach, as revealed by the the squared prediction errors. More importantly, the forecast comparison test reveals that the advantage of applying exogenous information related to climate risks in prediction of the South African stock return volatility is significant over a century of monthly data (February 1910–February 2023). Our findings have important implications for academics, investors, and policymakers.

Keywords: climate risks; volatility forecasting; model-free prediction; GARCH and GARCHX; South Africa

1. Introduction

Initially identified by [1], models of rare disasters have been proposed by [2], and later [3] to explain the equity premium puzzle. More recently, [4,5] have extended this line of research by studying models in which aggregate consumption mainly follows a low-volatility normal distribution, while a far out-in-the-left-tail realization of consumption can materialize with some probability, thereby giving rise to a disaster risk. Disaster risk not only raises the equity premium, but its time variation also produces high stock market volatility. Moreover, in another recent contribution, [6] builds on the literature on inattention to develop a model in which rare disaster risks magnify uncertainty, as well as its persistence. In this model, agents prepare for different future states of the world by collecting information, where they optimally ignore events that they think are sufficiently unlikely, implying that a realization of such an event does not resolve but raises uncertainty. As a result, when agents are endowed with dispersed beliefs, uncertainty acts as a catalyst of uncertainty and, thereby, creates endogenous persistence.

The traditional present discounted value model of asset prices [7,8] implies that asset price volatility depends on the variability of cash flows and the discount factor. Because an uncertain economic environment will tend to affect the volatility of future cash flows [9] and the discount factor [10], one can hypothesize a positive predictive relationship between uncertainty, originating from rare disaster events, and stock market volatility. In other words, well-established theoretical channels exist that warrant a detailed empirical analysis

of the link between rare disaster risk and stock market volatility. We lay out in this research the results of such an empirical analysis.

Our objective is to forecast stock return volatility of an important emerging market economy, namely South Africa, using the informational content of rare disaster risk, over the monthly period from February 1910 to February 2023. In line with the burgeoning literature on climate finance, we use changes in the temperature anomaly and its volatility as an empirical proxy of the theoretical concept of rare disaster risk, as in the advanced financial market movements-based research by [11–15], given that climate change poses a large aggregate risk to the overall macroeconomy and the global financial system due to the associated occurrences of rare disasters originating from physical risks involved with global warming and climate change [16–18]. To this end, we study data that span more than a century because climate change is a slow-moving process and its effects have tended to aggravate over time as economies have become more and more industrialized. Note that the term temperature anomaly means a departure from a reference value or long-term average, with a positive (negative) anomaly indicating that the observed temperature was warmer (cooler) than the reference value. Naturally, changes in the temperature anomaly and its volatility, capturing fluctuation in temperature from a "normal" scenario, can be considered as a metric of risks associated with extreme weather events.

It must be realized that, traditionally, disaster events are generally captured by cumulative declines in output and/or consumption of at least 10% over one or more years [19,20]. Given this, a major obstacle to full-fledged empirical testing of rare disaster models is that individual countries typically do not face such major disasters very often, resulting in a small sample problem inherent in the use of actual rare disasters, which, in turn, explains why earlier researchers studying the implications of rare disasters for asset pricing have relied on theoretical models calibrated on rare-disaster-risk probabilities derived from historical cross-country evidence of major declines in output and/or consumption. But, as indicated above, physical risks associated with climate change due to changes in the temperature anomaly and its volatility can solve the small sample problem, making the empirical estimation of such models feasible, especially when we look at long spans of data [21,22], which is the approach that we undertake. In other words, temperature anomaly changes and its volatility serve as an empirical proxy of the theoretical concept of rare disaster risks, while simultaneously also allowing us to study the effect of climate change on asset prices by associating global warming as a rare disaster event in the general equilibrium setup of disaster risks. In other words, changes in the temperature anomaly and its volatility serve as metrics of rare disaster risks that have both theoretical and empirical foundations in relation to movements in asset prices.

At this stage, it must be noted that, our choice of South Africa as a case study of an emerging market economy is motivated not only by the availability of stock market data spanning over a century but also because, as stressed by [23,24], a standalone analysis of the South African stock market is warranted due to its high degree of sophistication. In addition, South Africa is one of the largest exporters of strategic commodities such as coal, chrome, diamond, gold, ilmenite, iron ore, manganese, palladium, platinum, rutile, vanadium, vermiculite, and zirconium. While being a major global commodity exporter, and given the importance of the mining industry for its economy (which contributes roughly 8% of its gross domestic product (GDP), as per the Facts & Figures Pocketbook 2022 of the Minerals Council South Africa, see https://www.mineralscouncil.org.za/special-features/1345-facts-figures-pocketbook-2022 (accessed on 15 January 2024) for reference), the South African economy is run primarily on fossil fuel (coal)-generated energy, so that the country ranks as fourteenth and first in terms of carbon dioxide emissions in the world and Africa (see https://www.statista.com/ (accessed on 15 January 2024) for reference). Moreover, because South Africa is a semi-arid country, a global average temperature increase of 1.5 °C would correspond to a 3 °C increase of the average local temperature and, thereby, raise the likelihood of the risk of extreme weather events in the country (see report from Boston Consulting Group at: https://www.bcg.com/publications/2022/how-south-

african-mining-can-address-climate-change-challenges (accessed on 15 January 2024). It should be noted that transition risks of climate change stemming from the adoption of "green" technology-based production processes also have the potential to adversely impact the South African mining industries and, hence, the overall economy, which, in turn, could enhance the risk profile of the financial market of South Africa. But our objective is not to investigate such an indirect link in this paper, with our focus being climate-change related rare disaster-based physical risks and stock market volatility).

Evidently, the prominence of climate-related disaster risk for South Africa, and the potential influence of such a risk on its stock market volatility, is indeed a pertinent issue, as appropriate modeling and out-of-sample prediction of stock market volatility is important due to several reasons (as outlined, for example, by [25,26]). Firstly, modern finance theory implies that volatility is a key input to investment decisions and portfolio choices. Secondly, volatility is a key input to standard pricing formulas for derivative securities. For example, in order to price an option, one needs reliable estimates of the volatility of the underlying asset. Thirdly, financial risk management, according to the Basel Accord established as early as 1996, requires modeling and forecasting of volatility as a compulsory input to risk-management models used by financial institutions around the world. Last, but not least, stock market volatility, as was evident during the global financial crisis and the recent COVID-19 pandemic, can have severe repercussions on the economy as a whole via its effect on real economic activity and public confidence. Thus, forecasts of stock market volatility can serve as a measure of the vulnerability of the overall financial system and the whole economy and, thereby, can help policymakers design appropriate preventive policies.

Not surprisingly, the academic literature on the stock market volatility in South Africa, in terms of econometric methods, primarily involving variations of the generalized autoregressive conditional heteroskedasticity (GARCH) family, and predictors being considered, is quite abundant, to say the least (see, the citations in Section 2). However, despite the wide variation of econometric methods that researchers have used and the plethora of predictors that they have considered, no research has yet been performed on the role of climate risks in forecasting South African stock return volatility. In light of the fact that changes in temperature and its volatility can have strong general equilibrium effects [27–30], these predictors are likely to encompass the information contained in a wide array of macroeconomics and financial (and even behavioral [31,32]) predictors that have been used in earlier research to forecast stock price volatility in South Africa, with the added advantage that data on changes in temperature and its volatility have been available in a consistent manner for over 110 years.

Having said this, like [33], we control for the role of fundamentals- and sentiments-based information via the West Texas Intermediate (WTI) oil and precious metals (gold and silver) prices. The oil price (or its returns) is a good proxy of macroeconomic and financial predictors because of its potential to move stock prices through its impact on changes in expected cash flows and/or the discount rate, output, monetary and fiscal policy, and macroeconomic and financial uncertainties [34,35]. Gold, in turn, serves the dual role of a consumption good as jewelry and investors regarding it as a "safe haven" asset, i.e., investors consider it valuable in times of severe financial turmoil. In contrast, silver is a precious metal that, while having similar uses as gold in consumption, lacks the status of a "safe haven" asset. It follows that the ratio of gold-to-silver prices should be largely unaffected by consumption shocks. Rather, it should reveal variation in risk, with this price ratio rising when investor sentiment is weak and/or investors become more risk-averse [36]. The idea emanates from the gold-to-platinum price ratio proposed by [37] to capture global risk, given that data on platinum prices only stretch back to 1968. In the context of research on the predictability of South African stock market volatility, outlined in the next segment, several types of primarily univariate GARCH models and, when exogenous predictor(s) are added, GARCHX models have been utilized. While we also implement these models studied in earlier research, we go beyond earlier literature in that we also use the recently developed model-free method, NoVaS, which applies normalizing and variance-stabilizing

transformation (NoVaS transformation) to perform volatility predictions. We use one variant of the NoVaS method to study the role of climate risks, as captured by changes in the temperature anomaly and/or its volatility, over and above oil returns and the gold-to-silver price ratio, in forecasting stock return volatility in South Africa. In other words, our paper not only makes an important empirical contribution while analyzing the role of climate change in shaping the risk profile of a mining-intensive emerging market economy for the first time, but also does so by using recent methodological advances made in the context of volatility forecasting, and by using the recent focus on the NoVaS approach. While using long sample data has its attractiveness, especially when it comes to analyzing climate risks given their slow evolution, it also can be restrictive when it comes to availability of data associated with other predictors, i.e., fundamentals and behavioral. While we try to circumvent the concerns of an omitted variables bias by using innovative global proxies for these local economic conditions, we must concede that, while we think that this is not a serious limitation of our work, the oil returns and gold-to-silver price ratio are indeed imperfect proxies. Having said this, with climate risks known to lead a wide array of macroeconomic variables, changes in the temperature anomaly and its volatility surely contain local information on the state of the economy and, hence, oil returns and gold-to-silver price ratio movements can also be considered to be capturing global risks.

We organize the remainder of this research as follows. In Section 2, we cite the relevant papers associated with forecasting stock return volatility in South Africa, while, in Section 3, we describe the forecasting models we use in our empirical research. In Section 4, we outline our model evaluation criteria. After discussing the data in Section 5, we report our empirical results in Section 6. In Section 7, we conclude and discuss the implications of our findings.

2. Brief Discussion of Stock Return Volatility Literature of South Africa

In order to model and predict the volatility of the South African stock market, researchers have traditionally used various variants of the popular GARCH model. A comprehensive review of this literature is beyond the scope and objective of this paper, but the interested reader can refer to the works of [33,38–52], and the references cited therein. In terms of the international literature on modeling and predictability of stock market volatility, see [33,53–57] for detailed reviews. In these studies, researchers have thus far utilized either univariate approaches, especially when dealing with daily data, as well as various macroeconomic and financial predictors when modeling low-frequency, i.e., monthly, volatility. However, researchers thus far have not incorporated the role of changes in the temperature anomaly and its volatility capturing climate-based rare disaster risks in forecasting stock return volatility in South Africa spanning over a century of historical equity market data. In fact, in earlier studies on climate risks and stock markets, researchers primarily have concentrated on developed countries and on in-sample movements of the first moment [13,15,27,29,30], with the only exception being [14], who have analyzed stock market volatility of the state-level data in the United States (US). When it comes to volatility, the literature thus far has concentrated on predicting second moments of commodity returns due to climate risks (for example,[58–63]). Another somewhat related paper is that of [64], who have forecasted indicators of financial stress, comprised of both first and second moments of the underlying assets, of developed countries. In our paper, we thus take an emerging market perspective in this regard, using the well-utilized GARCH models in the South African volatility literature, but we also add the newly proposed NoVaS transformation method to our forecasting setup. This approach builds on the model-free prediction principle, first proposed by [65], which, in turn, has been shown to outperform a wide array of models from the GARCH-class in terms of volatility forecasting (see, for example, [66–68]). Motivated by the superior performance of the newly developed model-free GARCH-NoVaS model, [69] have extended this framework to a model that renders it possible to incorporate exogenous predictors, which, in turn, forms our motivation for the forecasting exercise that we undertake here.

3. Forecasting Models

3.1. Classical Models

The classic GARCH(1,1) model, as proposed by [70], can be described as follows:

$$
\begin{aligned}
Y_t &= \sigma_t W_t, \\
\sigma_t^2 &= a + a_1 Y_{t-1}^2 + b_1 \sigma_{t-1}^2,
\end{aligned}
\tag{1}
$$

where $a \geq 0$, $a_1 > 0$, $b_1 > 0$, and $W_t \sim i.i.d.\ N(0,1)$. After including a vector of exogenous covariates, $\boldsymbol{X} = (X_1, \ldots, X_m)$, we can wrap the exogenous covariates into the prediction process by turning the GARCH(1,1) model into the following GARCHX(1,1,1) model:

$$
\begin{aligned}
Y_t &= \sigma_t W_t, \\
\sigma_t^2 &= a + a_1 Y_{t-1}^2 + b_1 \sigma_{t-1}^2 + \boldsymbol{c}^T \boldsymbol{X}_{t-1},
\end{aligned}
\tag{2}
$$

where $\boldsymbol{X}_{t-1}$ represents $(X_{1,t-1}, \ldots, X_{m,t-1})$ and $\boldsymbol{c}$ are the coefficients of these exogenous variables to be estimated (see [71] for an in-depth discussion on the properties of such a GARCHX(1,1,1) model). In order to implement a moving-window out-of-sample prediction experiment with classical methods, we first need to estimate the GARCH(1,1) and GARCHX(1,1,1) models. For estimation of the GARCH and GARCHX models, we use the *fGarch* [72] and *garchx* packages [73] for the *R* language and environment for statistical computing [74], and then we compute predictions iteratively (see Section 4 for details).

3.2. NoVaS-Type Models

We next present two model-free prediction methods that have been developed recently—the GARCH-NoVaS and GARCHX-NoVaS models. These models are guided by the model-free prediction principle and rely on the normalizing and variance-stabilizing transformation (NoVaS transformation) to perform predictions.

3.2.1. GARCH-NoVaS Model

We first introduce the GARCH-NoVaS model, which is built on Equation (1). We focus on the parsimonious GARCH-NoVaS model proposed by [68]. The corresponding transformation and inverse transformation functions can be written as follows:

$$
W_t = \frac{Y_t}{\sqrt{\alpha s_{t-1}^2 + \sum_{i=1}^{q} \tilde{c}_i Y_{t-i}^2}} \ ; \ Y_t = \sqrt{W_t^2 \left(\alpha s_{t-1}^2 + \sum_{i=1}^{q} \tilde{c}_i Y_{t-i}^2 \right)},
\tag{3}
$$

where α is a constant that plays a similar role to the constant parameter, a, in Equation (1); s_{t-1}^2 is the sample variance of $\{Y_1, \ldots, Y_{T-1}\}$; the parameter q is a large enough constant (we use 20 in our empirical research), and $\{\tilde{c}_1, \ldots, \tilde{c}_q\}$ represents $\{a_1, a_1 b_1, a_1 b_1^2, \ldots, a_1 b_1^{q-1}\}$ scaled by multiplying with a scalar $\frac{1-\alpha}{\sum_{j=1}^{q} a_1 b_1^{j-1}}$.

In short, the model-free prediction principle is about a distribution-match problem. Assuming that we have observed one series, $\{Y_1, \ldots, Y_T\}$, we transform this series to another series, $\{\epsilon_1, \ldots, \epsilon_T\}$, with *i.i.d.* components (chosen as standard normal in this paper) through an invertible transformation function, H_T. Because the prediction of *i.i.d.* components is a trivial matter given a L_1 (MSE) or L_2 (MAE) loss criterion, we can obtain the optimal predictor of ϵ_{T+1} first and then transform it back to the prediction of Y_{T+1} with the inverse function H_T^{-1}. As for the GARCH-NoVaS model, we have ready-made transformation functions H_T and H_T^{-1}, as shown in Equation (3). Thus, our goal is to determine the coefficients $\{\tilde{c}_1, \ldots, \tilde{c}_q\}$ such that Equation (3) indeed demonstrates appropriate transformation functions. We decompose this problem into two parts: (1) variance stabilization, which is used to obtain unity variance; and (2) normalization, which is used to create *i.i.d.* components. Due to the fact that the transformed series from the financial

log-returns is usually uncorrelated, the transformation from the original series to the *i.i.d.* series can be guaranteed by integrating these two parts. Due to the rescaling manipulation, $\alpha + \sum_{i=1}^{p} \tilde{c}_i = 1$, which serves to satisfy the requirement of variance stabilization, the optimal combination of α, a_1, b_1 is selected by minimizing $|KURT(W_t) - 3|$ to satisfy the normalizing requirement; here, $KURT(W_t)$ is the kurtosis of the transformed series $\{W_t\}$. Empirically, $\{W_t\}$ is usually symmetrical, thus the kurtosis can be a simple metric to describe the distance between the distribution of $\{W_t\}$ and the standard normal distribution. Also, normalizing the marginal distribution is sufficient in our analysis.

After having determined the coefficients of this transformation function, we can apply the model-free prediction idea to set up our forecasting experiment. For example, if we consider the one-step-ahead prediction with observed $\{Y_1, \ldots, Y_T\}$, we can first represent Y_{T+1} by W_{T+1} and $\mathcal{F}_T$, which is the sigma-field of observed $\{Y_1, \ldots, Y_T\}$, i.e.,

$$Y_{T+1} = \sqrt{W_{T+1}^2 \left(\alpha s_T^2 + \sum_{i=1}^{q} \tilde{c}_i Y_{T+1-i}^2\right)} = f_{\text{GA}}(W_{T+1}, \mathcal{F}_T), \tag{4}$$

where we use f_{GA} to denote that the above representation is derived from the GARCH-NoVaS method. The ideal case is that we know F_W, which is the distribution of W_t, and then we can approximate the distribution of Y_{T+1} by simulating W_{T+1} from F_W. Similarly for multi-step ahead predictions, we can represent Y_{T+h} by $\{W_{T+1}, \ldots, W_{T+h}\}$ and $\mathcal{F}_T$ as $Y_{T+h} = f_{\text{GA}}(W_{T+1}, \ldots, W_{T+h}, \mathcal{F}_T)$. If F_W is known, we can still simulate the vector $\{W_{T+1}, \ldots, W_{T+h}\}$ from F_W and approximate the distribution of Y_{T+h}. However, we can only capture the distribution of W_t by $\widehat{F}_W$, which is the empirical distribution of the transformed series in practice. Therefore, we have to replace the simulation technique with the bootstrap, i.e., we bootstrap M (taken as 2000 in this paper) sets of $\{W_{T+1,m}^*, \ldots, W_{T+h,m}^*\}_{m=1}^{M}$ from $\widehat{F}_W$. Then, we can approximate the optimal predictor of Y_{T+h} as follows:

$$\begin{aligned} &L_1 \text{ optimal predictor: Median of } \{f_{\text{GA}}(W_{T+1,m}^*, \ldots, W_{T+h,m}^*, \mathcal{F}_T); m = 1, \ldots, M\}; \\ &L_2 \text{ optimal predictor: } \frac{1}{M} \sum_{m=1}^{M} f_{\text{GA}}(W_{T+1,m}^*, \ldots, W_{T+h,m}^*, \mathcal{F}_T). \end{aligned} \tag{5}$$

Moreover, using the continuing mapping theorem, we can further approximate the optimal prediction of $g(Y_{T+h})$ for any continuous function, $g(\cdot)$.

3.2.2. GARCHX-NoVaS Model

Recently, [69] have extended the GARCH-NoVaS model to include exogenous variables, that is, they have developed a so-called GARCHX-NoVaS model via similar steps to find the transformation function of the GARCH-NoVaS model. In order to simplify the notation, we consider the case of only one exogenous covariate, X_t. The case of multiple exogenous covariates can be analyzed analogously. In line with the GARCH-NoVaS transformation, we write the transformation function, H_T, corresponding with the GARCHX-NoVaS method as follows:

$$W_t = \frac{Y_t}{\sqrt{\alpha s_{t-1,Y}^2 + \beta s_{t-1,X}^2 + \sum_{i=1}^{p} a_1 b_1^{i-1} Y_{t-i}^2 + \sum_{i=1}^{p} c_1 b_1^{i-1} X_{t-i}}}, \tag{6}$$

where $s_{t-1,Y}^2$ and $s_{t-1,X}^2$ are the sample variance of $\{Y_1, \ldots, Y_{t-1}\}$ and $\{X_1, \ldots, X_{t-1}\}$, respectively. We set $p = q$ in our empirical research. Guided by the model-free prediction principle, the plan is to optimize the coefficients according to the variance stabilization and normalization requirement to obtain a qualified transformed series and its corresponding empirical distribution, $\widehat{F}_W$. Also, we can express Y_{T+h} as

$$Y_{T+h} = f_{\text{GAX}}(W_{T+1}, \ldots, W_{T+h}, \mathcal{F}_T, \mathcal{F}_{X,T+h}), \tag{7}$$

where $\mathcal{F}_{X,T+h}$ is the sigma-field of $\{X_1, \ldots, X_{T+h}\}$ (we should notice that we assume that we know the future exogenous variables). Thus, the multi-step-ahead predictions of the GARCHX-NoVaS method can be computed by applying the same bootstrap approach as described in Section 3.2.1. See [69] for more details on the development of the GARCHX-NoVaS model.

4. Model Evaluation

In order to evaluate the prediction performance of the different models, we consider two measures: (1) the sum of squared prediction errors (SSPE), with this statistic aiming to compare the prediction performance in an absolute way, and (2) the CW test statistic proposed by [75], which, in turn, can be used to compare the forecasting performance of two nested models, i.e., to test whether a parsimonious null model and a larger model have equal predictive accuracy.

In order to define a suitable SSPE metric for long-term predictions ($h > 1$), we consider the below time-aggregated predictions, as studied by [67], to measure the forecasting performance of the different models at an overall level (for other applications of this approach, see [76,77]):

$$\overline{\widehat{Y}}_{T,h}^2 = \sum_{k=1}^{h} (\widehat{Y}_{T+k}^2/h))^2, \tag{8}$$

where $\overline{\widehat{Y}}_{T,h}^2$ is the h-step ahead time-aggregated volatility prediction for $\{T+1, \ldots, T+h\}$. In order to fully exhaust the dataset (which consists of a total of N observations), we further focus on moving-window out-of-sample predictions, i.e., we use $\{Y_1, \cdots, Y_T\}$ to predict $\{Y_{T+1}^2, \cdots, Y_{T+h}^2\}$, then we use $\{Y_2, \cdots, Y_{T+1}\}$ to predict $\{Y_{T+2}^2, \cdots, Y_{T+h+1}^2\}$, and so on until we reach the end of the sample (that is, until we use $\{Y_{N-T+h+1}, \cdots, Y_{N-h}\}$ to predict $\{Y_{N-h+1}^2, \ldots, Y_N^2\}$). Here, T denotes the moving window size, which we fix at values between 240 and 500 in our empirical study. Thus, we can define the SSPE with the time-aggregated metric as below:

$$P = \sum_{l=T}^{N-h} (\overline{\widehat{Y}}_{l,h}^2 - \sum_{k=1}^{h} (Y_{l+k}^2/h))^2, \tag{9}$$

where $\overline{\widehat{Y}}_{l,h}^2$ denotes the time-aggregated prediction for each moving window forecast and $\sum_{k=1}^{h}(Y_{l+k}^2/h)$ denotes the corresponding realized average squared returns.

In addition to this numerical comparison, we consider the CW test proposed by [75] to verify whether the parsimonious null model and the nested model have equal predictive accuracy. For further details on the CW test, especially its application in the context of the type of analysis we consider in our empirical research, we refer the reader to the research by [69,75].

5. Data

We aim to predict the volatility of the Johannesburg Stock Exchange (JSE) All Share Index (ALSI) (JSE-ALSI) with the raw data of the index obtained from Global Financial Data (GFD) (https://globalfinancialdata.com/ (accessed on 15 January 2024)). To this end, we convert the raw data to log-returns in percentages. The data for the controls of fundamentals- and sentiments-based information, i.e., the WTI oil, gold, and silver prices, are used to generate the log-returns (OR) of the oil price, and the ratio of the gold-to-silver prices (GS). The corresponding raw data were obtained from GFD and Macrotrends (https://www.macrotrends.net/ (accessed on 15 January 2024)).

The temperature anomaly (relative to a historical mean over 1991–2020) data for South Africa, upon specifying its coordinates, i.e., stretching latitudinally from 22° S to 35° S and longitudinally from 17° E to 33° E, is available from the National Oceanic and Atmospheric Administration (NOAA), see https://www.ncei.noaa.gov/access/monitoring/climate-

at-a-glance/global/time-series (accessed on 15 January 2024). We work with the first difference of the temperature anomaly and also apply the GARCH or NoVaS models to obtain the corresponding conditional volatilities of the temperature anomaly series to be used as an additional measure of climate risks. In particular, to capture climate risks, we compute the month-on-month change of the temperature anomaly, i.e., DTA, as well as the year-on-year change, i.e., DYTA, to avoid any concerns regarding seasonal effects.

Before analyzing the different forecasting models, we first check the properties of the log-returns, DTA, and DYTA to see whether the series indeed are heteroskedastic. We plot the three time series in Figure 1.
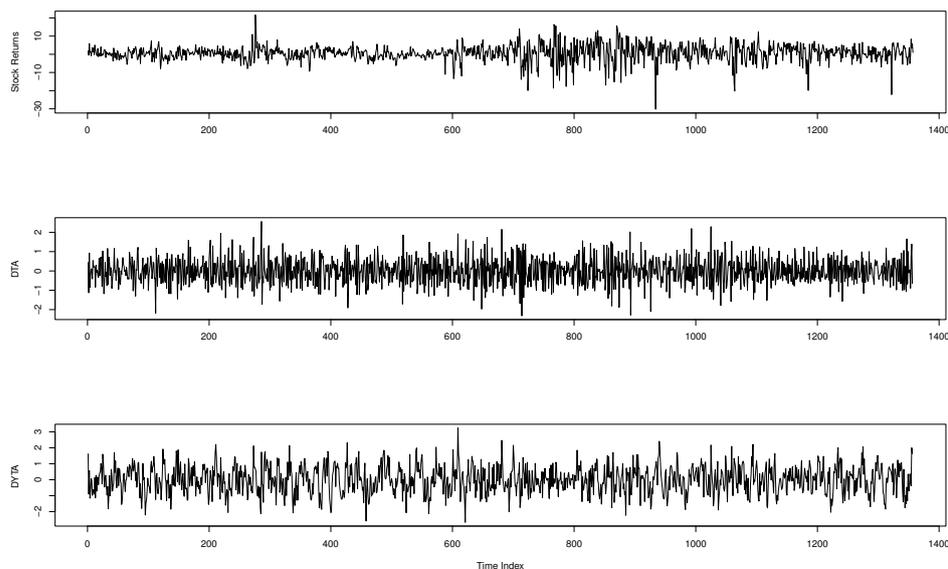

Figure 1. Plots of stock log-returns, DTA, and DYTA.

Looking at Figure 1, a volatility clustering phenomenon is quite obvious. For example, there are relatively strong fluctuations in stock returns for the time index from 200 to 400, and 800 to 1000. For the DYTA series, relatively strong fluctuations appear around time index 600. In order to statistically validate this phenomenon, we apply the McLeod and Li (ML) test [78]. The null hypothesis of the ML test is that there is no autoregressive conditional heteroskedasticity among the lags considered. The test, when applied to our data, produces *p*-values of near zero for all lags considered until the maximum (i.e., 31) allowed by the function "McLeod.Li.test" in *R* from the *TSA* package [79], with details of the results available upon request from the authors. Hence, we detect strong evidence of heteroskedasticity in the variables of our concern.

6. Empirical Results

In order to study the role played by oil log-returns, the ratio of the gold-to-silver prices, and climate risks, we include the different exogenous covariates in our forecasting models step by step and then distinguish four types of models:

- Stage-1 model: we apply the GARCH and GARCH-NoVaS models to compute predictions. These two models are the benchmark for classical and model-free type methods.
- Stage-2 model: we add OR and GS to the model. This results in GARCHX and GARCHX-NoVaS models with two covariates.
- Stage-3 model: we take DTA or DYTA data into account based on Stage 2 models. Meanwhile, we keep including OR and GS as exogenous variables.
- Stage-4 model: we estimate the volatilities of DTA and DYTA by means of GARCH or NoVaS models and then use the estimates as additional covariates. In order to simplify notation, we denote the volatility of DTA/DYTA estimated by a GARCH

model as DTAV1/DYTAV1, while we use DTAV2/DYTAV2 to denote the volatility of DTA/DYTA as estimated by means of a NoVaS model.

In order to fully exhaust the dataset, we consider moving-window out-of-sample predictions, i.e., we make predictions based on a sliding window with 240 or 500 observations. For the prediction horizon, we consider 1-, 3-, 6-, and 12-step-ahead horizons.

We report our empirical results in Tables 1–3. We summarize in Table 1 the results of a comparison of the Stage-1 model and the Stages 2-4 models, where the GARCH model is the benchmark model. In Table 2, we document the results of a comparison between the Stage-2 model and the Stage-3 models. We use the GARCHX Stage-2 model as the benchmark model. Similarly, we summarize in Table 3 the performance of the Stage-3 model relative to the Stage-4 model. In order to simplify the presentations of the SSPE, which is computed according to Equation (9), we divide the SSPE of the GARCH model by the SSPE of the other models and denote this ratio as the ratio of squared errors between those models and the benchmark, that is, we use this ratio to measure the relative performance of different models.

Table 1. Stage-1 comparisons.

	Ratio of Squared Errors				*p*-**Value of CW-Test**			
Prediction Step	**1**	**3**	**6**	**12**	**1**	**3**	**6**	**12**
Moving window size 500:								
GARCH (Benchmark)	1.000	1.000	1.000	1.000				
GARCH-NoVaS	0.998	0.957	0.883	0.746				
GARCHX-2	1.000	1.004	0.998	0.987	0.087	0.036	0.014	0.003
GARCHX-NoVaS-2	0.995	0.959	0.881	0.732	0.061	0.032	0.000	0.000
Moving window size 240:								
GARCH (Benchmark)	1.000	1.000	1.000	1.000				
GARCH-NoVaS	1.070	1.025	0.908	0.684				
GARCHX-2	1.023	1.060	1.092	1.059	0.449	0.401	0.349	0.030
GARCHX-NoVaS-2	0.990	0.934	0.842	0.644	0.041	0.000	0.000	0.000

Note: GARCHX-2 and GARCHX-NoVaS-2 are Stage-2 models where the OR and GS information is involved in the prediction process based on the parsimonious model GARCH or NoVaS.

Table 2. Stage-2 comparisons.

	Ratio of Squared Errors				*p*-**Value of CW-Test**			
Prediction Step	**1**	**3**	**6**	**12**	**1**	**3**	**6**	**12**
Moving window size 500:								
GARCHX-2 (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-2	0.994	0.956	0.882	0.742				
GARCHX-3-DTA	1.000	1.000	1.005	0.996	0.386	0.309	0.986	0.102
GARCHX-NoVaS-3-DTA	1.004	0.947	0.878	0.732	0.894	0.001	0.013	0.000
GARCHX-3-DYTA	1.000	1.001	1.003	1.004	0.940	0.917	0.943	0.806
GARCHX-NoVaS-3-DYTA	0.997	0.955	0.882	0.734	0.525	0.143	0.187	0.001
Moving window size 240:								
GARCHX-2 (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-2	0.967	0.882	0.771	0.608				
GARCHX-3-DTA	1.002	1.003	1.006	0.996	0.837	0.787	0.929	0.154
GARCHX-NoVaS-3-DTA	0.968	0.887	0.772	0.602	0.234	0.473	0.240	0.042
GARCHX-3-DYTA	1.004	1.009	1.009	1.010	0.994	0.998	0.976	0.847
GARCHX-NoVaS-3-DYTA	0.963	0.888	0.770	0.601	0.070	0.723	0.192	0.023

Note: the Stage-3 model takes DTA/DYTA into account, e.g., GARCHX-3-DTA represents the Stage-3 GARCHX model with OR, GS, and DTA exogenous covariates.

Table 3. Stage-3 comparisons.

	Ratio of Squared Errors				*p*-Value of CW-Test			
Prediction Step	**1**	**3**	**6**	**12**	**1**	**3**	**6**	**12**
Moving window size 500:								
GARCHX-3-DTA (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-3-DTA	1.004	0.948	0.874	0.734				
GARCHX-4-DTAV1	1.001	1.000	0.995	0.992	0.576	0.298	0.037	0.014
GARCHX-NoVaS-4-DTAV1	1.001	0.960	0.881	0.749	0.156	0.991	0.721	0.960
GARCHX-4-DTAV2	1.000	0.999	0.993	0.990	0.419	0.103	0.001	0.002
GARCHX-NoVaS-4-DTAV2	0.999	0.962	0.876	0.743	0.081	0.993	0.404	0.808
GARCHX-3-DYTA (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-3-DYTA	0.997	0.953	0.879	0.731				
GARCHX-4-DYTAV1	1.000	1.000	0.998	0.999	0.974	0.371	0.144	0.357
GARCHX-NoVaS-4-DYTAV1	1.005	0.957	0.885	0.740	0.961	0.647	0.797	0.801
GARCHX-4-DYTAV2	1.000	0.999	1.002	0.997	0.891	0.205	0.823	0.133
GARCHX-NoVaS-4-DYTAV2	1.003	0.957	0.887	0.740	0.926	0.581	0.882	0.808
Moving window size 240:								
GARCHX-3-DTA (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-3-DTA	0.966	0.884	0.766	0.603				
GARCHX-4-DTAV1	1.003	1.003	0.999	1.015	0.789	0.811	0.269	0.923
GARCHX-NoVaS-4-DTAV1	0.973	0.880	0.756	0.585	0.762	0.091	0.008	0.005
GARCHX-4-DTAV2	1.001	1.000	1.001	1.003	0.700	0.481	0.477	0.516
GARCHX-NoVaS-4-DTAV2	0.977	0.882	0.761	0.585	0.941	0.176	0.066	0.008
GARCHX-3-DYTA (Benchmark)	1.000	1.000	1.000	1.000				
GARCHX-NoVaS-3-DYTA	0.960	0.880	0.763	0.593				
GARCHX-4-DYTAV1	1.000	1.001	0.997	0.994	0.879	0.691	0.069	0.184
GARCHX-NoVaS-4-DYTAV1	0.965	0.867	0.752	0.562	0.777	0.002	0.053	0.001
GARCHX-4-DYTAV2	1.001	1.001	1.004	1.005	0.945	0.864	0.861	0.640
GARCHX-NoVaS-4-DYTAV2	0.967	0.872	0.752	0.580	0.853	0.012	0.026	0.020

Note: the Stage-4 model further considers the volatility of DTA and DYTA by taking the Stage-3 model as the parsimonious one. We use DTAV1 and DTAV2 to represent the volatility of DTA estimated by GARCH and NoVaS models, respectively. We can explain the meanings of DYTAV1 and DYTAV2 similarly. For example, GARCHX-4-DYTAV1 represents the Stage-4 GARCHX model with OR, GS, and DYTA, and volatility of DYTA estimated by GARCH.

The following results emerge from our forecasting experiment:

- *The effects of OR and GS:* the role of fundamentals- and sentiments-based information is revealed by the comparison of the Stage-1 and -2 models in Table 1. Taking the GARCH model as the benchmark, the Stage-2 GARCH model performs better when we use the SSPE statistic to evaluate 6- and 12-step-ahead predictions (moving window of size 500). The results of the CW test corroborate that the MSPE of the GARCH Stage-2 model is significantly smaller in a statistical sense than that of the benchmark model. However, for the moving window with 240 observations, the benchmark model beats the Stage-2 GARCH model. One reason may be that the sample size is not large enough to obtain a satisfactory estimation of the GARCHX model. However, OR and GS are also statistically beneficial to the predictions when we study the NoVaS method. Moreover, this improvement can also be observed for the 240-moving window.
- *The effects of DTA/DYTA:* the results that we report in Table 2 show that, for GARCH-type models, with a 500- or 240-moving window, the improvement in SSPE brought about by including DTA or DYTA in the models is negligible. Actually, the Stage-2 GARCH model outperforms the Stage-3 GARCH model, irrespective of whether we study DTA or DYTA, for 1-, 3-, and 6-step-ahead predictions. The corresponding CW tests are not significant. The NoVaS-type models, however, can utilize climate information to yield more accurate forecasts. For example, the GARCHX-NoVaS-3-

DTA model is better than the corresponding Stage-2 NoVaS model when we use a 500-moving window. The corresponding CW test also implies that we can reject the null hypothesis. However, the gain in forecast accuracy is hardly visible for predictions based on a 240-moving window, but it is still statistically significant at a significance level of 0.05. According to our results, DTA is more useful when the moving window size is 500, and DYTA is more useful for a 240-moving window.

- *The effects of volatilities of DTA/DYTA:* according to Table 3, the volatility of DTA and DYTA is almost useless in improving the forecast accuracy of the GARCHX models, and almost all CW tests when applied to the corresponding Stage-3 and -4 models cannot reject the null hypothesis. Interestingly, the NoVaS-type models produce some forecasting benefits after including the volatility of DTA or DYTA, especially for long prediction horizons and a short moving window. For two types of volatility, DTAV1 and DYTAV2, the forecasts are slightly more accurate than their counterparts estimated by the NoVaS model.

- *The effects of applying the model-free NoVaS prediction technique:* it is evident from Tables 1–3 that the NoVaS-type models are much better than the corresponding GARCH models for all four stages, and, hence, our work adds to the general literature on stock return volatility forecasting in South Africa that has primarily relied on the GARCH framework. More importantly, when we add climate risks to the NoVaS model, we observe that forecasting performance improves. The classical GARCH model, however, fails to take advantage of the information embedded in these covariates. All in all, the combination of the temperate anomaly and its volatility captured by a GARCH model gives the best model (Stage-4 NoVaS) due to its large MSE accuracy and robustness. Our findings thus corroborate the importance of climate risks in driving historical second-moment movements of an emerging stock market, i.e., South Africa, just like what was detected for the US and other advanced economies by [14,64]. In the process, we confirm that the role of physical risks due to changes in the temperature anomaly and its volatility acting as proxies of rare disaster events can be associated with the theoretical idea of the predictive relationship between asset market volatility and disaster risks.

7. Conclusions

We have studied, using a dataset that covers more than a century, the contribution of climate risks to the accuracy of forecasts of stock return volatility based on data for South Africa, an important emerging market economy. We have measured climate risks by studying the temperature anomaly and/or its volatility. Our findings show that climate risks do have predictive value for stock market volatility, where the novel model-free prediction method (GARCHX-NoVaS) can incorporate the information embedded in climate data better than classical methods, as witnessed by the result that the NoVaS models that include climate information achieve a stronger improvement in forecast accuracy than GARCH-type models, and the fact that the NoVaS model with the volatility of changes in the temperature anomaly estimated by the GARCH approach is the best model in terms of the forecast evaluation criterion and its robustness.

As outlined in the introductory part (Section 1), appropriate modeling and accurate forecasting of volatility based on factors (predictors) has ample implications for portfolio selection, the pricing of derivative securities, and risk management, making it a metric of paramount importance to not only investors but also policymakers. Hence, our findings indicate that the local climate risks can assist in terms of the above-mentioned pertinent issues in South Africa, over the above information contained in (proxies of) fundamentals and sentiments. Academically speaking, we provide empirical confirmation of the theoretical predictions that link rare disaster risks, modeled through weather patterns, with stock return volatility, in an emerging market setting. In this regard, from a statistical perspective, we also show the role of a model-free approach in appropriately capturing and predicting volatility.

As part of future research, it is interesting to extend our work to other emerging market economies, conditional on the availability of long spans of historical data, as well as to the currency markets of South Africa, and other fossil-fuel exporters, building on the work by [80]. Also, we should mention that the success of the NoVaS method depends on a good transformation result. The transformation may be adversely impacted by some extreme values and is restricted by the transformation complexity of the NoVaS method. Thus, it is also interesting to apply the NoVaS method with state-of-the-art techniques, such as deep neural networks.

Author Contributions: conceptualization, R.G. and C.P.; methodology, K.W. and S.K.; software, K.W.; validation, R.G., C.P., S.K. and K.W.; formal analysis, K.W. and S.K.; investigation, R.G. and C.P.; resources, R.G.; data curation, R.G.; writing—original draft preparation, K.W. and S.K.; writing—review and editing, R.G., C.P., S.K. and K.W.; visualization, K.W.; supervision, R.G., S.K. and C.P.; project administration, R.G.; funding acquisition, S.K. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: The data used in this paper can be found through the link in Section 5.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Mehra, R.; Prescott, E.C. The equity premium: A puzzle. *J. Monet. Econ.* **1985**, *15*, 145–161. [CrossRef]
2. Rietz, T.A. The equity risk premium a solution. *J. Monet. Econ.* **1988**, *22*, 117–131. [CrossRef]
3. Barro, R.J. Rare disasters and asset markets in the twentieth century. *Q. J. Econ.* **2006**, *121*, 823–866. [CrossRef]
4. Wachter, J.A. Can time-varying risk of rare disasters explain aggregate stock market volatility? *J. Financ.* **2013**, *68*, 987–1035. [CrossRef]
5. Tsai, J.; Wachter, J.A. Disaster risk and its implications for asset pricing. *Annu. Rev. Financ. Econ.* **2015**, *7*, 219–252. [CrossRef]
6. Sundaresan, S. Emergency Preparation and Uncertainty Persistence. *Manag. Sci.* **2023** . [CrossRef]
7. Shiller, R.J. Do stock prices move too much to be justified by subsequent changes in dividends? *Am. Econ. Rev.* **1981**, *75*, 421–436.
8. Shiller, R.J. The use of volatility measures in assessing market efficiency. *J. Financ.* **1981**, *36*, 291–304.
9. Bernanke, B.S. Nonmonetary effects of the financial crises in the propagation of the Great Depression. *Am. Econ. Rev.* **1983**, *73*, 257–276.
10. Schwert, G.W. Why does stock market volatility change over time? *J. Financ.* **1989**, *44*, 1115–1153. [CrossRef]
11. Balvers, R.; Du, D.; Zhao, X. Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *J. Bank. Financ.* **2017**, *77*, 18–34. [CrossRef]
12. Donadelli, M.; Jüppner, M.; Paradiso, A.; Ghisletti, M. Tornado activity, house prices, and stock returns. *N. Am. J. Econ. Financ.* **2020**, *52*, 101162. [CrossRef]
13. Balcilar, M.; Gabauer, D.; Gupta, R.; Pierdzioch, C. Climate Risks and Forecasting Stock Market Returns in Advanced Economies over a Century. *Mathematics* **2023**, *11*, 2077. [CrossRef]
14. Bonato, M.; Çepni, O.; Gupta, R.; Pierdzioch, C. Climate risks and state-level stock market realized volatility. *J. Fin. Mark.* **2023**, *66*, 100854. [CrossRef]
15. Salisu, A.A.; Pierdzioch, C.; Gupta, R.; Van Eyden, R. Climate risks and US stock-market tail risks: A forecasting experiment using over a century of data. *Int. Rev. Financ.* **2023**, *23*, 228–244. [CrossRef]
16. Giglio, S.; Kelly, B.; Stroebel, J. Climate finance. *Annu. Rev. Financ. Econ.* **2021**, *13*, 15–36. [CrossRef]
17. Stroebel, J.; Wurgler, J. What do you think about climate finance? *J. Financ. Econ.* **2021**, *142*, 487–498. [CrossRef]
18. van Benthem, A.A.; Crooks, E.; Giglio, S.; Schwob, E.; Stroebel, J. The effect of climate risks on the interactions between financial markets and energy companies. *Nat. Energy* **2022**, *7*, 690–697. [CrossRef]
19. Ćorić, B. Economic disasters: A new data set. *Financ. Res. Lett.* **2021**, *39*, 101612. [CrossRef]
20. Ćorić, B.; Šimić, V. Economic disasters and aggregate investment. *Empir. Econ.* **2021**, *61*, 3087–3124. [CrossRef]
21. Bansal, R.; Kiku, D.; Ochoa, M. *Price of Long-Run Temperature Shifts in Capital Markets*; National Bureau of Economic Research: Cambridge, MA, USA, 2021.
22. Bansal, R.; Ochoa, M.; Kiku, D. Climate change and growth risks. In *Climate Change Economics: The Role of Uncertainty and Risk; The Role of Uncertainty and Risk in Climate Change Economics*; Chari, V.V., Litterman, R., Eds.; Wiley: Hoboken, NJ, USA, 2017.

23.	Mensi, W.; Hammoudeh, S.; Reboredo, J.C.; Nguyen, D.K. Do global factors impact BRICS stock markets? A quantile regression approach. *Emerg. Mark. Rev.* **2014**, *19*, 1–17. [CrossRef]

24.	Mensi, W.; Hammoudeh, S.; Yoon, S.M.; Nguyen, D.K. Asymmetric linkages between BRICS stock returns and country risk ratings: Evidence from dynamic panel threshold models. *Rev. Int. Econ.* **2016**, *24*, 1–19. [CrossRef]

25.	Poon, S.H.; Granger, C.W.J. Forecasting volatility in financial markets: A review. *J. Econ. Lit.* **2003**, *41*, 478–539. [CrossRef]

26.	Rapach, D.E.; Strauss, J.K.; Wohar, M.E. Forecasting stock return volatility in the presence of structural breaks. In *Forecasting in the Presence of Structural Breaks and Model Uncertainty*; Emerald Group Publishing Limited: Leeds, UK, 2008.

27.	Donadelli, M.; Jüppner, M.; Riedel, M.; Schlag, C. Temperature shocks and welfare costs. *J. Econ. Dyn. Control* **2017**, *82*, 331–355. [CrossRef]

28.	Donadelli, M.; Grüning, P.; Jüppner, M.; Kizys, R. Global temperature, R&D expenditure, and growth. *Energy Econ.* **2021**, *104*, 105608.

29.	Donadelli, M.; Jüppner, M.; Paradiso, A.; Schlag, C. Computing macro-effects and welfare costs of temperature volatility: A structural approach. *Comput. Econ.* **2021**, *58*, 347–394. [CrossRef]

30.	Donadelli, M.; Jüppner, M.; Vergalli, S. Temperature variability and the macroeconomy: A world tour. *Environ. Resour. Econ.* **2022**, *83*, 221–259. [CrossRef]

31.	Sheng, X.; Gupta, R.; Cepni, O. Persistence of state-level uncertainty of the United States: The role of climate risks. *Econ. Lett.* **2022**, *215*, 110500. [CrossRef]

32.	Cepni, O.; Gupta, R.; Liao, W.; Ma, J. Climate risks and forecastability of the weekly state-level economic conditions of the United States. *Int. Rev. Financ.* **2024**, *24*, 154–162. [CrossRef]

33.	Salisu, A.A.; Gupta, R. Commodity prices and forecastability of international stock returns over a century: Sentiments versus fundamentals with focus on South Africa. *Emerg. Mark. Financ. Trade* **2022**, *58*, 2620–2636. [CrossRef]

34.	Degiannakis, S.; Filis, G.; Arora, V. Oil prices and stock markets: A review of the theory and empirical evidence. *Energy J.* **2018**, *39*, 85–130. [CrossRef]

35.	Smyth, R.; Narayan, P.K. What do we know about oil prices and stock returns? *Int. Rev. Financ. Anal.* **2018**, *57*, 148–156. [CrossRef]

36.	Salisu, A.A.; Pierdzioch, C.; Gupta, R.; Gabauer, D. Forecasting stock-market tail risk and connectedness in advanced economies over a century: The role of gold-to-silver and gold-to-platinum price ratios. *Int. Rev. Financ. Anal.* **2022**, *83*, 102300. [CrossRef]

37.	Huang, D.; Kilic, M. Gold, platinum, and expected stock returns. *J. Financ. Econ.* **2019**, *132*, 50–75. [CrossRef]

38.	Moolman, E.; Du Toit, C. An econometric model of the South African stock market: Economics. *S. Afr. J. Econ. Manag. Sci.* **2005**, *8*, 77–91. [CrossRef]

39.	Mangani, R. Modelling return volatility on the JSE securities exchange of South Africa. *Afr. Financ. J.* **2008**, *10*, 55–71.

40.	Samouilhan, N.; Shannon, G. Forecasting volatility on the JSE. *Investig. Anal. J.* **2008**, *37*, 19–28. [CrossRef]

41.	Babikir, A.; Gupta, R.; Mwabutwa, C.; Owusu-Sekyere, E. Structural breaks and GARCH models of stock return volatility: The case of South Africa. *Econ. Model.* **2012**, *29*, 2435–2443. [CrossRef]

42.	Chinzara, Z. Macroeconomic uncertainty and conditional stock market volatility in South Africa. *S. Afr. J. Econ.* **2011**, *79*, 27–49. [CrossRef]

43.	Mandimika, N.Z.; Chinzara, Z. Risk–return trade-off and behaviour of volatility on the south african stock market: Evidence from both aggregate and disaggregate data. *S. Afr. J. Econ.* **2012**, *80*, 345–366. [CrossRef]

44.	Afuecheta, E.; Pérez Ruiz, D.A.; Utazi, C.; Nwosu, C. On the flexibility of GARCH-family models with an application to the BRICS stock indices. *Commun. Stat. Case Stud. Data Anal. Appl.* **2016**, *2*, 44–77. [CrossRef]

45.	Sigauke, C.; Volatility modeling of the JSE all share index and risk estimation using the Bayesian and frequentist approaches. *Econ. Manag. Financ. Mark.* **2016**, *11*, 33–48.

46.	Cakan, E.; Gupta, R. Does the US macroeconomic news make the South African stock market riskier? *J. Dev. Areas* **2017**, *51*, 15–27.

47.	Cheteni, P. Stock market volatility using GARCH models: Evidence from South Africa and China stock markets. *J. Econ. Behav. Stud.* **2017**, *8*, 237–245. [CrossRef] [PubMed]

48.	Naik, P.K.; Gupta, R.; Padhi, P. The relationship between stock market volatility and trading volume: Evidence from South Africa *J. Dev. Areas* **2018**, *52*, 99–114. [CrossRef]

49.	Muzindutsi, P.-F.; Obalade, A.A.; Gaston, R.T. Financial crisis and stock return volatility of the JSE general mining index: GARCH modelling approach. *J. Account. Manag.* **2020**, *10*, 115–124.

50.	Dwarika, N.; Moores-Pitt, P.; Chifurira, R. Volatility dynamics and the risk-return relationship in South Africa: A GARCH approach. *Investig. Manag. Financ. Innov.* **2021**, *18*, 106–117. [CrossRef]

51.	Kaseke, F.; Ramroop, S.; Mwambi, H. A comparative analysis of the volatility nature of cryptocurrency and JSE market. *Investig. Manag. Financ. Innov.* **2022**, *19*, 23–39. [CrossRef]

52.	Gupta, R.; Nel, J.; Pierdzioch, C. Drivers of Realized Volatility for Emerging Countries with a Focus on South Africa: Fundamentals versus Sentiment. *Mathematics* **2023**, *11*, 1371. [CrossRef]

53.	Ben Nasr, A.; Boutahar, M.; Trabelsi, A. Fractionally integrated time varying GARCH model. *Stat. Methods Appl.* **2010**, *19*, 399–430. [CrossRef]

54.	Ben Nasr, A.; Ajmi, A.N.; Gupta, R. Modelling the volatility of the Dow Jones Islamic Market World Index using a fractionally integrated time-varying GARCH (FITVGARCH) model. *Appl. Financ. Econ.* **2014**, *24*, 993–1004. [CrossRef]

55. Bhowmik, R.; Wang, S. Stock market volatility and return analysis: A systematic literature review. *Entropy* **2020**, *22*, 522. [CrossRef]

56. Muguto, L.; Muzindutsi, P.F. A comparative analysis of the nature of stock return volatility in BRICS and G7 markets. *J. Risk Financ. Manag.* **2022**, *15*, 85. [CrossRef]

57. Segnon, M.; Gupta, R.; Wilfling, B. Forecasting stock market volatility with regime-switching GARCH-MIDAS: The role of geopolitical risks. *Int. J. Forecast.* **2023**, *40*, 29–43. [CrossRef]

58. Bouri, E.; Gupta, R.; Pierdzioch, C.; Salisu, A.A. El Niño and forecastability of oil-price realized volatility. *Theor. Appl. Climatol.* **2021**, *144*, 1173–1180. [CrossRef]

59. Demirer, R.; Gupta, R.; Nel, J.; Pierdzioch, C. Effect of rare disaster risks on crude oil: Evidence from El Niño from over 145 years of data. *Theor. Appl. Climatol.* **2022**, *147*, 691–699. [CrossRef]

60. Gupta, R.; Pierdzioch, C. Climate risks and forecastability of the realized volatility of gold and other metal prices. *Resour. Policy* **2022**, *77*, 102681. [CrossRef]

61. Bonato, M.; Çepni, O.; Gupta, R.; Pierdzioch, C. El Niño, La Niña, and forecastability of the realized variance of agricultural commodity prices: Evidence from a machine learning approach. *J. Forecast.* **2023**, *42*, 785–801. [CrossRef]

62. Gupta, R.; Pierdzioch, C. Climate Risk and the Volatility of Agricultural Commodity Price Fluctuations: A Forecasting Experiment. In *Behavioral Finance and Asset Prices: The Influence of Investor's Emotions*; Bourghelle, D., Grandin, P., Jawadi, F., Rozin, P., Eds.; Springer: Berlin/Heidelberg, Germany, 2023; Chapter 2.

63. Nel, J.; Gupta, R.; Wohar, M.E.; Pierdzioch, C. Climate Risks and Predictability of Commodity Returns and Volatility: Evidence from over 750 Years of Data. Forthcoming in Climate Change Economics. Available online: https://www.up.ac.za/media/shared/61/WP/wp_2022_42.zp224084.pdf (accessed on 15 January 2024).

64. Del Fava, S.; Gupta, R.; Pierdzioch, C.; Rognone, L. Forecasting international financial stress: The role of climate risks. *J. Int. Financ. Mark. Inst. Money* **2024**, *92*, 101975. [CrossRef]

65. Politis, D.N. A normalizing and variance-stabilizing transformation for financial time series. In *Recent Advances and Trends in Nonparametric Statistics*; Elsevier Inc.: Amsterdam, The Netherlands, 2003; pp. 335–347.

66. Gulay, E.; Emec, H. Comparison of forecasting performances: Does normalization and variance stabilization method beat GARCH (1, 1)-type models? Empirical Evidence from the Stock Markets. *J. Forecast.* **2018**, *37*, 133–150. [CrossRef]

67. Wu, K.; Karmakar, S. Model-free time-aggregated predictions for econometric datasets. *Forecasting* **2021**, *3*, 920–933. [CrossRef]

68. Wu, K.; Karmakar, S. A model-free approach to do long-term volatility forecasting and its variants. *Financ. Innov.* **2023**, *9*, 1–38. [CrossRef]

69. Wu, K.; Karmakar, S. GARHCX-NoVaS: A Model-free Approach to Incorporate Exogenous Variables. *arXiv* **2023**, arXiv:2308.13346.

70. Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *J. Econom.* **1986**, *31*, 307–327. [CrossRef]

71. Francq, C.; Thieu, L.Q. QML inference for volatility models with covariates. *Econom. Theory* **2019**, *35*, 37–72. [CrossRef]

72. Wuertz, D.; RUnit, S.; Chalabi, M.Y. *Package 'fGarch'*; Technical Report, working Paper/Manual, 09.11; 2013. Available online: https://CRAN.R-project.org/package=fGarch (accessed on 15 January 2024).

73. Sucarrat, G. garchx: Flexible and robust garch-x modelling. *R J.* **2021**, *13*, 267–291. [CrossRef]

74. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2023.

75. Clark, T.E.; West, K.D. Approximately normal tests for equal predictive accuracy in nested models. *J. Econom.* **2007**, *138*, 291–311. [CrossRef]

76. Chudý, M.; Karmakar, S.; Wu, W.B. Long-term prediction intervals of economic time series. *Empir. Econ.* **2020**, *58*, 191–222. [CrossRef]

77. Karmakar, S.; Chudý, M.; Wu, W.B. Long-term prediction intervals with many covariates. *J. Time Ser. Anal.* **2022**, *43*, 587–609. [CrossRef]

78. McLeod, A.I.; Li, W.K. Diagnostic checking ARMA time series models using squared-residual autocorrelations. *J. Time Ser. Anal.* **1983**, *4*, 269–273. [CrossRef]

79. Chan, K.S.; Ripley, B.; Chan, M.K.S.; Chan, S. *Package 'TSA'*, R Package Version 1.31; 2022. Available online: https://CRAN.R-project.org/package=TSA (accessed on 15 January 2024).

80. Bonato, M.; Çepni, O.; Gupta, R.; Pierdzioch, C. Climate risks and realized volatility of major commodity currency exchange rates. *J. Financ. Mark.* **2023**, *62*, 100760. [CrossRef]