Climate Risks and U.S. Stock-Market Tail Risks: A Forecasting Experiment Using over a Century of Data

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Abstract

We examine the predictive value of the uncertainty associated with growth in temperature for stock-market tail risk in the United States using monthly data that cover the sample period from 1895:02 to 2021:08. To this end, we measure stock-market tail risk by means of the popular Conditional Autoregressive Value at Risk (CAViaR) model. Our results show that accounting for the predictive value of the uncertainty associated with growth in temperature, as measured either by means of standard generalized autoregressive conditional heteroskedasticity (GARCH) models or a stochastic-volatility (SV) model, mainly is beneficial for a forecaster who suffers a sufficiently higher loss from an underestimation of tail risk than from a comparable overestimation.

JEL classification: C22, C53, G10

Keywords: Stock market, Tail risks, Climate risks, Forecasting, Asymmetric loss

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1 Introduction

Climate change, associated with increased temperature as well as its volatility, poses a large aggregate risk to the economy and the financial system of the United States (U.S.) due to the occurrences of rare disasters (Giglio et al., 2021). In essence, disasters abound when temperature reaches or crosses a threshold level and capture the idea of tail-risk related to global warming (Pindyck, 2012). At the same time, macroeconomic developments in the U.S. play a key role for the world economy. Despite a declining share in world GDP, U.S.-based transnational corporations, and U.S. ownership of such corporations, play a leading or, depending on the sector that is being studied, even a dominant role, implying that the extent of globalization of the U.S. economy cannot be downplayed (Starrs, 2013). It is, therefore, not surprising that developments in the U.S market mirror the dynamics of the global economy, and that any shock that hits the U.S. economy, such as the financial crisis of 2007, will unfold a reverberating impact on the global economy. Meanwhile, following the rise in the demand for water and cooling in the U.S. in the wake of severe mega-droughts (Stahle et al., 2000, 2007), significant efforts have been undertaken to shed light on the effects of global climate change on various sectors of the U.S. economy (see, e.g., Karl et al., 2009; Knowlton et al., 2011). In particular, the nexus between climate change and exposure to extreme heat (temperature) is well established (Luber and McGeehin, 2008). In this process, the U.S. financial markets play a key role because, as also withnessed by the global financial crisis of 2007, they have the potential to pose systemic threats to global financial stability (Alvarez et al., 2020).

Against this background, quite a few recent studies (see for example, Donadelli et al. (2017; 2021a, b), Engle et al., (2020), Balvers et al., (2017), Bansal et al., (2021, forthcoming)) have extended general equilibrium models of rare disaster risks to incorporate climate risks driven by first- and second-moment shocks of growth in temperature to formalize the theoretical channels via which the economy and the stock market is impacted. For example, Balvers et al. (2017) argue that temperature shocks arising due to uncertainty of climate change raise the cost of equity, and subsequently, result in a loss of wealth. In the same vein, Donadelli et al. (2021a) argue that temperature-volatility shocks undermine equity valuations and produce non-negligible welfare costs. Peillex et al (2021) show that extreme heat above 300^oC depresses stock-market activity and, thereby, market returns (Hou et al., 2019). In general, the results of these significant research efforts indicate that climate risk tends to reduce productivity and/or the stochastic depreciation rate of capital, and also affects investors' propensity to trade *via* its implications for distraction, mood, etc., to produce an adverse impact on macroeconomic variables and equity valuations.[1] According to this line of research in behavioral finance, the nexus between temperature, mood, and investor behaviour works, on the one-hand side, through the temperature-aggression channel, where lower temperature leads to aggression and propensity to engage in a more risky venture. On the other-hand side, higher temperature leads to apathy which depresses risk-taking behaviour (Cao and Wei, 2005). The foregoing suggests a negative relationship between temperature and stock returns. This has equally been validated in some other empirical literature (Floros, 2011; Piard, 2013; He and Ma, 2021). In contrast to the foregoing, another line of literature establishes a positive nexus (Makkonen et al., 2021) while others submit a no-relationship between the two variables (Jacobsen and Marquering, 2008; Lu and Chou, 2012; Chandra, 2021).

The key assumption underlying rare-disaster models is that the entire universe of assets in an economy is exposed to an aggregate jump-risk factor. It follows that, even though in the cross section, some assets are more exposed to such a tail event than others, such a jump-risk factor should be an important driver of the time-series variation in the tails of individual asset returns (Rietz, 1988; Barro, 2006, 2009). In other words, we can hypothesize that the jump-risk factor associated with the dynamics of the mean and the volatility of the growth of temperature, i.e., climate risks, has predictive power for movements in the tail risks of the aggregate stock market.[2] Tail risks have been shown to lead stock returns and real-economic-activity-related variables (Kelly and Jiang, 2014; Almeida et al., 2017; Chevapatrakul et al., 2019; Hollstein et al., 2019;

[1]Based on the suggestion of an anonymous referee, using data on total factor productivity and capital intensity (serving as a proxy for the stochastic depreciation rate), derived from the Long Term Productivity Database (`http://www.longtermproductivity.com/`) of Bergeaud et al., (2016), we were able to provide some preliminary evidence, based on a Vector Autoregressive model, featuring as endogenous variables the growth in temperature, its volatility, growth in total factor productivity, capital intensity, and stock returns, that climate-risks shocks tend to affect the latter three variables negatively. Complete details of these results are available upon request from the authors.

[2]By definition, tail risk is the additional risk that commonly observed fat-tailed asset-returns distributions exhibit relative to a normal distribution (Li and Rose, 2009).

Salisu et al., Forthcoming a).[3] Understandably, deducing the future path of tail risks in real-time is an important question for both investors and policymakers (Gkillas et al., 2021; Gupta et al., 2021).

Against this backdrop, given that out-of-sample forecasting is considered to be a more robust test of predictability compared to an in-sample analysis in terms of the predictors and econometric model being used (Campbell, 2008), the objective of our empirical research is to analyze the role of the growth and conditional volatility (obtained from generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic-volatility (SV) models, following Alessandri and Mumtaz (2021)) of temperature in the U.S. for forecasting stock-market tail risks over the monthly period from 1895:02 to 2021:08. By studying data over the longest possible sample period, we not only avoid the issue of a potential sample-selection bias, but, more importantly, we can also accurately analyze the effect of the slowly-evolving historical temperature and its volatility on tail risks. This motivation to use over 125 years of data also makes the choice of the U.S. an obvious one due to data availability on both temperature and stock price. In this regard, instead of the traditionally used option-implied measures of tail risks (Salisu et al., 2022b), we use a framework based on the underlying returns data measure tail risk, which is understandable due to the unavailability of data on options over the prolonged sample period that we study in this research. Specifically, we estimate tail risk using the popular Value at Risk (VaR) metric at 1% and 5% by employing the conditional autoregressive quantile specification as proposed by Engle and Manganelli (2004), which, in turn, is called the CAViaR model(as a robustness check, we also draw on extreme-value theory (EVT) to estimate a GARCH-EVT-based model). Equipped with estimates of stock-market tail risk, we then rely on an autoregressive predictive framework characterized by symmetric and asymmetric forecaster loss functions to assess the predictive power of the growth rate of temperature as well as its volatility for forecasting stock-market tail risk.

It is important to note that in case we do detect evidence of forecastability of tail risk generated from climate-risks-related variables, then we would provide an additional channel via which

[3] Salisu et al. (2021, 2022a) emphasize the role of stock-market tail risks in driving oil prices, and its tail risks.

rare-disaster events associated with movements in temperature is likely to drive, and in turn, prolong the impact on the macroeconomy and financial markets of the U.S. – an information that should be of immense value to traders and policy authorities alike. To the best of our knowledge, this is the first paper to forecast over a century of tail risks of the U.S. stock market by accounting for the role of climate risks. The only somewhat related (published) paper is that of De Nicolò and Lucchetta (2017),[4] wherein the authors present a set of multi-period forecasts of indicators of real (industrial production and employment growth) and financial (distance to insolvency measures of corporate and banking sectors) tail risks obtained using a large database of monthly U.S. data for the sample period from 1972:01 to 2014:12. De Nicolò and Lucchetta (2017) document that forecasts obtained with autoregressive (AR) and factor-augmented vector autoregressive (FAVAR) models significantly underestimate tail risks. Quantile projections, in contrast, deliver more accurate forecasts and reliable early-warning signals up to a 1-year horizon. As discussed above, with climate-related risks shown to affect a wide array of important macroeconomic and financial variables, the growth of temperature and its conditional volatility used in this study for forecasting stock-market tail risk can be considered to encompass the information in many, if not all, of the predictors studied by De Nicolò and Lucchetta (2017).

We organize the remainder of our paper as follows. In Section **??**, we describe the data and methodologies used in our empirical analysis. In Section **??**, we discuss the empirical results. In Section **??**, we conclude.

2 Data and Methodologies

2.1 Data

In order to estimate the U.S. stock-market tail risk, we use the monthly S&P500 stock-price index.[5] We convert the index data into log-returns in percentages (i.e., the first-difference of the

[4]Besides this, Salisu et al. (2022c, forthcoming b) forecast in a couple of recent working papers historical tail risks of advanced stock markets, including that of the U.S., using oil-tail risks, a world-fear index (computed from tail-risks spillovers), and gold-to-silver and gold-to-platinum price ratios serving as proxies of global risks.

[5]We downloaded the the data from the online data-segment of the website of Professor Robert J. Shiller (`http://www.econ.yale.edu/~shiller/data.htm`).

natural logarithm of the index multiplied by 100, which we denote as SR). The temperature data is the average of the 48 contiguous U.S. states, from which we compute its growth rate (GT). The raw temperatures data is available from National Oceanic and Atmospheric Administration (NOAA).[6] With temperature data available from 1895:01, our analysis starts from 1895:02 (even though the S&P500 index is available from 1871), since we lose one observation due to the computation of the growth rate of temperature.

We use the Exponential GARCH (EGARCH) model of Nelson (1991) to estimate the conditional volatility of the growth rate of temperature.[7] The EGARCH model fits the data best among alternative symmetric and asymmetric models belonging to the GARCH-family.[8] In order to assess the sensitivity of our results with respect to the specification of the EGARCH model, we consider two EGARCH models. Specifically, we extract GARCH-1, our first estimate of the conditional volatility, by regressing the growth rate of temperature only on a constant in the conditional-mean equation of the EGARCH model. We derive GARCH-2, in turn, by including one lag of the growth rate, besides the constant, in the conditional-mean equation.[9]

Though our focus is on forecasting tail risks based on the two metrics of climate risks, i.e., GT and GARCH-1 (and GARCH-2), to motivate the analysis and the fact that GT and GARCH-1 indeed can affect tail risks of the US stock market, we provide some preliminary evidence of the lagged effect of the two climate risks metrics on SR. For this purpose, we use the quantile-on-

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[6] See https://www.ncdc.noaa.gov/cag/national/time-series.

[7] The EGARCH model stipulates that the conditional variance of a stochastic process $\{\varepsilon_t\}$ can be modeled as follows: $y_t - \phi_0 - (\sum_{i=1}^{r} \phi_i y_{t-i}) - (\sum_{i=1}^{m} \theta_i \varepsilon_{t-i}) = \varepsilon_t = \sigma_t Z_t$, with $\ln(\sigma_t^2) = \ln(Var(\varepsilon_t|\mathscr{F}_{t-1})) = \alpha_0 + \sum_{i=1}^{q} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - E\left(|Z_{t-i}|\right)\right)\right) + \sum_{i=1}^{p} \beta_i \ln\left(\sigma_{t-i}^2\right)$, where y_t is the variable (in our case growth of temperature) for which the conditional volatility is to be derived, Z_t is a white noise, independent of the σ-field ($\mathscr{F}_{t-1}$) for all t with mean zero and variance 1, and $E\left(|Z_t|\right)$ is the conditional expectation with respect to density function $f(z)$: $E\left(|Z_t|\right) = \int_{-\infty}^{\infty} |z| f(z) \mathrm{d}z$. The EGARCH model captures the asymmetric dynamics through the term $g(z_{t-i}) = \alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - E\left(|Z_{t-i}|\right)\right)$. The ARCH effect term, $g(z_t)$ is linear in z_t with slope $\alpha + \gamma$ for $z_t > 0$ and $\alpha - \gamma$ for $z_t < 0$.

[8] Complete details of all these estimations are available from the authors upon request .

[9] It should be noted that the GARCH-2 model makes the estimate of the volatility of the growth rate of temperature comparable with the one derived from the stochastic-volatility model (which we discuss in Footnote **??**), which also includes a lag of the growth rate of temperature.

quantile regression approach of Sim and Zhou (2015),[10] which allows the quantiles-based (δ_1) response of SR to depend on the magnitude, i.e., quantiles of GT and GARCH-1 (δ_2). As can be seen from Figure **??**, in general, the effect of the first lag of GT and GARCH-1 on SR is negative over the various quantiles of both the independent and dependent variables (δ_2 and δ_1 respectively), but the effect is particularly strong at the higher quantiles of GARCH-1. These findings provide us with initial indication that climate risks are expected to enhance tail risks of the US stock market by negatively impacting its returns.

– Figure **??** about here. –

2.2 Methodologies

The CAViaR framework developed by Engle and Manganelli (2004) is used the compute the U.S. stock market tail risks. An interesting feature of this approach relative to others[11] is due to the fact that it focuses on the asymptotic form of the tail, rather than the whole distribution. The generic representation for the CAViaR is of the following format:

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_j l(x_{t-j}) \tag{1}$$

where $f_t(x_{t-1}, \beta_\theta)$, which is compactly written as $f_t(\beta)$ in Equation (**??**), denotes the period θ-quantile of the distribution of stock returns formed at $t-1$. The function $f_t(\beta)$ does not include θ for notational convenience. The dimension of β is given as $p = q + r + 1$ to reflect the combination of $\sum_{i=1}^{q} \beta_i f_{t-i}(\beta)$ and $\sum_{j=1}^{r} \beta_j l(x_{t-j})$. While the term $f_t(\beta)$ is linked to x_{t-j} of a finite number of lagged values of observables using the function $l(x_{t-j})$, the term , $\beta_i f_{t-i}(\beta)$, $i = 1, ..., q$, is included to ensure that the quantile changes “smoothly" over time. There are four

[10]The technically minded reader is referred to this paper to get an understanding of the details of this methodology

[11]Other approaches such as those proposed by Boudoukh et al., (1998) and Danielsson and de Vries (2000) are not “extreme enough" to capture the tail distribution.

specifications of the CAViaR model (i.e., the Adaptive, Symmetric absolute value, Asymmetric slope and Indirect GARCH specifications) and they are represented as follows:[12]

1. Adaptive:

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1[1 + exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta. \tag{2}$$

2. Symmetric absolute value:

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3|y_{t-1}|. \tag{3}$$

3. Asymmetric slope:

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3(y_{t-1})^+ + \beta_4(y_{t-1})^-. \tag{4}$$

4. Indirect GARCH (1,1):

$$f_t(\boldsymbol{\beta}) = (\beta_1 + \beta_2 f_{t-1}^2(\boldsymbol{\beta}) + \beta_3 y_{t-1}^2)^{1/2}. \tag{5}$$

In Equation (**??**), the last term converges almost surely to $\beta_1[I(y_{t-1} \leq f_{t-1}(\beta_1)) - \theta]$ if $G \to \infty$, with $I(\cdot)$ denoting the indicator function. Note that a smoothed version of a step function in Equation (**??**) is modeled with some positive finite number, G . The Symmetric absolute value and the Indirect GARCH specifications are symmetric, while the third specification given above is asymmetric. It follows that the response to positive and negative returns is identical for the former, but differs for the latter. Finally, it is worth mentioning that while the coefficient of the lagged VaR in the adaptive specification is constrained to unity, the other three specifications are not, and, as a result, are considered to be mean reverting.

We use all the four CAViaR specifications to produce results for both the 1% and the 5% VaRs, and then we compute as diagnostics the %Hits, the Dynamic Quantile (DQ) test, and the Regression Quantile (RQ) statistic to determine the "optimal" CAViaR specification. For the "optimal"

[12]Technically-minded readers may refer to Engle and Manganelli (2004) for further details on the tail-risk estimation. Also, recent applications of the CAVaiR framework to measure tail risks are documented in the energy-finance literature by Salisu et al., (2021, 2022a, b, c, forthcoming a, b).

specification, the %Hits should be close to 1% for 1% VaR and 5% for 5% VaR, the DQ test statistic should be insignificant, and the the RQ loss function should be minimized (i.e., a smaller RQ statistic is better).[13]

In order to examine the predictive value of growth in temperature and its volatility for stock-market tail risk, we estimate the following forecasting model by the ordinary-least-squares technique (OLS):

$$TR_{t+h} = c + \theta TR_t + X_t^{'}\gamma + \eta_{t+h}, \tag{6}$$

where η_{t+h} denotes a disturbance term. The nucleus of this forecasting model is a simple autoregressive model, with coefficients c and θ. The predictand, TR_{t+h}, is the average value of TR_t over the forecasting horizon, where we consider three forecast horizons: $h = 1,3,6$ months. Moreover, X_t denotes a vector of additional predictors (that is, temperature growth, its conditional volatility, or both), and γ denotes the corresponding appropriately dimensioned vector of coefficients to be estimated.

In order to account for the possibility that the coefficients of the forecasting model may have changed during our sample period, which covers more than a century of monthly data, we estimate Equation (**??**) by means of a recursively expanding estimation window, where we use the first ten years of monthly data to initialize the estimations.

The main tool we use to evaluate the forecasting performance of the forecasting model specified in Equation (**??**) is the asymmetric loss function proposed by Elliott et al. (2005, 2008). This asymmetric loss function nests the standard symmetric loss function as a special case and, in addition, accounts for the possibility that a forecaster incurs a higher (or lower) loss from under-estimating tail risk than from over-estimating it by the same absolute magnitude. The loss function is given by $\mathscr{L} = [\alpha + (1-2\alpha)\mathbf{1}(TR - \hat{TR} < 0)]|TR - \hat{TR}|^2$, where $\mathbf{1}$ denotes the indicator function, and $\hat{TR}$ denotes the forecast of stock-market tail risk.[14] The parameter, $\alpha \in (0,1)$,

[13]We assume that the DQ test takes prominence over the %Hits and the RQ statistics. In cases where more than one tail risk is statistically insignificant in terms of the DQ test, we consider both the %Hits and the RQ statistics to identify the specification with the best fit.

[14]We have dropped the time index for notational convenience.

governs the asymmetry of the loss function. For $\alpha = 0.5$, the loss function degenerates to a standard symmetric quadratic loss function. For $\alpha \neq 0.5$, we obtain an asymmetric loss function. Upon setting $\alpha > 0.5$ ($\alpha < 0.5$), the loss from under-estimating (over-estimating) tail risk exceeds the loss from an overestimation (underestimation) of the same (absolute) magnitude.[15]

3 Empirical Results

3.1 Baseline Results

In order to set the stage for our forecasting experiment, we compute the 1% and 5% stock-market tail risks using the four CAViaR specifications (Symmetric Absolute Value, Asymmetric Slope, Indirect GARCH and Adaptive) described in Section **??**. As mentioned in Section **??**, we use standard diagnostics to determine the "optimal" CAViaR specification. We report the results in Table **??**. For both the the 1% and 5% VaRs, we find that the Asymmetric Slope specification fits the data best, using the %Hits, the DQ test, and the RQ test statistics. Hence, we use the tail risks computed by means of the Asymmetric Slope model in our forecasting analysis. Figure **??** plots the estimated 1% and 5% tail risks.

– Figure **??** and Tables **??** and **??** about here. –

Table **??** depicts baseline forecasting results. Specifically, we report in Panels A and B the results for the ratio of root-mean-squared-forecasting error (RMSFE) as the ratio of the RMSFE of the benchmark autoregressive model and a rival model that includes the variables displayed in the first column as additional predictors. In Panels C and D, we report the of p-values of the

[15]It should be noted that we do not use the loss function to draw conclusions regarding the "rationality" of forecasts under (as-)symmetric loss. The sole purpose of the (asymmetric) loss function is to shed light on whether different types of (or investors) benefit to different extents from forecasts. The main idea behind the loss function, thus, is that, while the standard squared-error loss function restricts attention to the "symmetric" type, the preferences of other types of forecasters (for example, investors or portfolio managers who use one-sided option trading strategies and, thus, benefit or suffer to a different extent from an over-estimation or under-estimation of tail risk) may be better described in terms of an asymmetric loss function.

Clark and West (2007) test for an equal out-of-sample mean-squared prediction error (MSPE). In Panels E and F, we report p-values of the modified version of the Diebold and Mariano (1995) test proposed by Harvey et al. (1997). In order to compute out-of-sample forecasts, we use a recursive-estimation window, where we start with a training period of ten years to initialize the estimations. The forecast horizons are 1, 3, and 6 months, where for the latter two, we forecast the average tail risk over the forecast horizon. The key message conveyed by the results is that the rival models do not yield more accurate forecasts than the benchmark model. The RMSFE ratios are either smaller than or very close to unity and the Clark-West and Diebold-Mariano tests yield insignificant results in the majority of cases.

– Figure **??** about here. –

Figure **??** depicts the results for the modified Diebold-Mariano test that we obtain when we assume that a forecaster has a potentially asymmetric loss function of the type described in Section **??**.[16] We plot the p-values of the test on the vertical axis as a function of the asymmetry parameter, α, on the horizontal axis. Corroborating the results we report in Table **??**, the test results are insignificant when we set $\alpha = 0.5$. In addition, however, we observe that the p-values rapidly decrease and eventually become significant for those forecasting models that feature GARCH-2 (all three forecast horizons) or GARCH-1 (forecast horizons of three and six months) in the vector of predictor variables once we consider the possibility that the asymmetry parameter exceeds its symmetric benchmark value. Hence, accounting for temperature uncertainty (as measured by our GARCH models) when forecasting stock-market tail risk, is beneficial for a forecaster who suffers a higher loss from an under-estimation of tail risk than from an over-estimation of the same absolute size, where the value of the asymmetry parameter, α, that makes the test results significant at conventional significance levels differs across tail risks, forecasting models, and forecast horizons. Importantly, forecasts extracted from those models that only feature changes

[16]The asymmetric loss function does not imply that the forecasts become more "accurate" when we choose different numerical values for the asymmetry parameter. This follows from the fact that we do not use the loss function to compute forecasts (all forecasts are computed using a forecasting model estimated by the OLS technique) but rather the loss function attaches different weights to forecast errors depending on the numerical value of the asymmetry parameter.

in temperature as a predictor variable are not significantly more beneficial than the forecasts computed by means of the simple benchmark model, irrespective of the value we assign to the asymmetry parameter.

– Figure **??** about here. –

In order to build intuition, we study in Figure **??** the results for TR_1, a training period of ten years, and a forecast horizon of $h = 3$ in more detail (that is, this example corresponds to the results depicted in Figure **??**, Panel A, middle panel). We plot in the left-hand (middle) panel the mean (median) of the forecast error produced by the models given on the horizontal axis relative to the forecast error produced by the benchmark model (without climate predictors). The mean (median) increases as we move from the left to the right and, thereby, is larger for the forecasting models that use temperature uncertainty (especially GARCH-2) and/or the growth in temperature rather than for the model that only uses the growth in temperature as a predictor. In other words, the climate-extended forecasting models tend to produce, on average, a larger negative (or a smaller positive) forecast error than the benchmark model. This property of the climate-extended forecasting models is beneficial for a forecaster who attaches a larger weight to a positive forecast error (underestimation of tail risk) than to a negative forecast error of the same absolute magnitude. In order to illustrate this argument, we plot two loss functions in the right-hand panel for a shape parameter equal to $\alpha = 0.95$ (asymmetric loss function) and $\alpha = 0.5$ (asymmetric loss function). A forecaster whose preferences can be described in terms of the asymmetric loss function benefits from using a forecasting model that, when compared to a benchmark model, provides a better "hedge" against large positive forecast errors, that is, a model that shifts, on average, forecast errors to "the left"', which is exactly what the mean (median) indicate is the case for the forecasting models that feature the climate predictors. Because this "shift" is smaller for the forecasting model that features only the growth in temperature as an additional predictor than for the other climate-extended forecasting models, it is natural that the test results that we plot in the middle panel of Panel A of Figure **??** show that the "growth in temperature" forecasting model fares much worse in terms of the statistical significance of the test results in the range $\alpha > 0.5$ than the other climate-extended forecasting models.

3.2 Additional Results

It remains to assess the robustness of our results. We consider three robustness checks. First, we study a rolling-estimation window of length ten years as an alternative to the recursive-estimation window. Figure **??** depicts the results for a rolling-estimation window. The results for TR_1 are qualitatively in line with the results for the recursive-estimation window. For TR_5 the results are not significant for the short forecast horizon, and scratch the 10% line of significance when we study the intermediate and long forecast horizon. The shape of the p-value functions, however, shows a forecaster tends to incur a higher loss from an under-estimation of stock-market tail risk than from an over-estimation of the same absolute seize (that is, when α is sufficiently large), where the model that features GARCH-2 a predictor yields significant results also for the short forecast horizon.

– Figures **??** and **??** about here. –

Second, we consider a stochastic-volatility model as an alternative to the GARCH models. Figure **??** depicts the results for the stochastic-volatility (SV) model.[17] We observe that accounting for stochastic volatility of temperature growth is beneficial when α is sufficiently large, mainly for the short and intermediate forecast horizon. Importantly, changes in temperatures per se do no leverage the extent to which a forecaster with an asymmetric loss function benefits from forecasts.

Third, we measure stock-market tail risk using the Generalized Autoregressive Conditional Heteroscedasticity-Extreme Value Theory (GARCH-EVT) framework. This model is motivated by the often documented underestimation and overestimation of parametrically determined VaR and conditional

[17]Let us denote the growth in temperature by $y = (y_1, y_2, ..., y_T)'$, we follow Kastner and Früwirth-Schnatter (2014) and specify the SV model as: $y_t = e^{h_t/2}\varepsilon_t$, with $h_t = \mu + \psi(h_{t-1} - \mu) + \sigma\nu_t$, where the iid standard normal innovations ε_t and ν_s are by assumption independent for $t, s \in \{1, ..., T\}$. The unobserved process $h = (h_0, h_1, ..., h_T)$ that shows up in the state equation is interpreted as a latent time-varying volatility process with initial state distributed according to the stationary distribution, i.e., $h_0|\mu, \psi, \sigma \sim \mathcal{N}(\mu, \sigma^2/(1-\psi^2))$. Simulation efficiency can often be improved through model reparameterization. Following Kastner and Frühwirth-Schnatter (2014), the non-centered parameterization of the model is given by: $y_t \sim \mathcal{N}(0, \omega E_t^{\sigma\tilde{h}})$, with $\tilde{h}_t = \psi\tilde{h}_{t-1} + \nu_t, \qquad \nu_t \sim \mathcal{N}(0,1)$, where $\omega = e^{\mu}$. The initial value of $\tilde{h}_0|\psi$ is drawn from the stationary distribution of the latent process, i.e., $\tilde{h}_0|\psi \sim \mathcal{N}(0, 1/(1-\psi^2))$, and $\tilde{h}_t = (h_t - \mu)/\sigma$. Detailed estimation results for the stochastic-volatility model can be obtained from the authors upon request.

value at risks (CVaR), following the outcome of backtesting (see Dargiri et al., 2013; Chebbi and Hedhli, 2020). EVT has become useful in financial risk management (see McNeil and Frey, 2000) and is also widely adopted for the estimation of the VaRs of financial time series, given its characteristic focus on the tail behavior rather than the entire data points, and its improvement over extant conventional techniques for VaR estimation. We incorporate the EVT in a Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model, as a way to account for potential asymmetries in the series. Estimation of the GARCH-EVT model proceeds in three steps: (i.) We estimate an AR(1)-GJR-GARCH(1,1) model with innovations that follow the skewed student t-distribution; (ii.) We retrieve and standardize the model residuals; (iii.) We determine a threshold value and adopt the Generalized Pareto Distribution (GPD) to model the extreme values of the series being considered. Specifically, we adopt the peak-over threshold (POT) approach to ascertain the threshold value as well as the exceedances and shortfalls associated with the threshold value. The estimated scale and shape parameters (standard errors) for the GPD model are respectively -0.1124 (0.1053) and 0.5750 (0.0859). Considering the 95th percentile, the estimated threshold value is approximately 1.3847, with about 88 data points exceeding the threshold value, and a corresponding shortfall (expected size of loss) estimate of approximately 1.9054.

– Figures **??** about here. –

Panel A of Figure **??** depicts the estimated tail-risk series. The overall qualitative pattern (e.g.,the timing of peaks) that the GARCH-EVT based tail-risk measure exhibits does not differ markedly from that of the CAViaR-based tail-risk measures, while Panel B demonstrates that the test results for an asymmetric loss function qualitatively resemble those that we obtain for the other tail-risk measures.

4 Concluding Remarks

Results of recent empirical research show that stock-market tail risks do not only have predictive value for subsequent stock returns, but also for real economic activity. Given this predictive value, the objective of our research is to examine whether growth in temperature in general and uncertainty associated with it in particular help to forecast the tail risk of U.S. stock market returns, using monthly data for a sample period that ranges from 1895 to 2021. In order to model tail risks, we have employed variants of the popular CAViaR as this model concentrates on the tail distribution rather the whole distribution of stock returns.

In a first step, we have reported, in the context of an in-sample analysis, by means of a quantiles-on-quantiles model that climate risks are expected to enhance tail risks of the US stock market. The analysis using the quantiles-on-quantiles model has shown that the strength of the link between the growth in temperature and uncertainty, on the one hand, and stock market returns, on the other hand, exhibits a clear quantiles-dependent pattern. In a second step, we have shown by means of a simple out-of-sample forecasting experiment that accounting for growth in temperature in general and their uncertainty does not improve forecasting performance when we use standard symmetric summary statistics of forecast accuracy. Consistent with the quantiles-dependent pattern we have found using the quantiles-on-quantiles model, we have found significant benefits from using climate-related uncertainty to compute forecasts once we allow for the possibility that a forecaster has an asymmetric loss function. Specifically, our results demonstrate that a forecaster who incurs a higher loss from an under-estimation of stock-market tail risk than from an over-estimation of the same absolute size (that is, when the loss function is sufficiently asymmetric in the forecast error) benefits from using uncertainty associated with temperature growth rates for forecasting tail risk, where we have considered forecast horizons of up to six months and where we have measured uncertainty associated with growth in temperature by means of GARCH and SV models.

Our findings show that portfolio managers and policy makers who seek to develop a deeper understanding of the impact of climate-related risks for stock-market developments in general and stock-market tail risks in particular should not only focus on the link between tail risks and the growth in temperature and uncertainty on average but should rather consider the possibility that quantiles-dependent patterns are present in the data and that the impact of climate-related risks on stock-market tail risks, when studied by means of a simple and easy-to-implement linear forecasting models, only become visible once an asymmetric loss function is used to evaluate forecasts. Our results have shown that using such an asymmetric loss function should be particularly useful when a forecast consumer suffers a larger loss from an under-estimation of stock-market tail risk than from an over-estimation of the same absolute size. Such an "under-estimation is more important than over-estimation" scenario is a quite natural setting for policy makers who seek to implement policy measures that help to mitigate turbulence of real economic activity in the aftermath of stock market tail events. At the same time, an interesting question for future research is whether and, if so, how the accelerating shift towards climate-friendly and zero-emission policies will alter the nexus between the growth in temperature and uncertainty and (subsequent) stock-market tail risks. The empirical findings that we have reported in this research should be a useful and natural starting point for such analyses.

Another avenue for future research is to examine the predictive value of uncertainty of growth in temperature and other weather phenomena (like, e.g., the uncertainty stemming from a potential strike of a natural disaster) for stock-market tail risks in other advanced and emerging-market economies. Yet another important avenue for future research, especially from a systematic point of view, is to study whether uncertainty of temperature growth and other weather phenomena also affects the cross-country connectedness of stock markets and their tail risks. Finally, another avenue future research may take is to take the asymmetry we have documented in this research as a starting point for considering the link between stock-market tail risk and uncertainty of growth in temperature through the lens of non-linear forecasting models.

References

Alessandri, P., and Mumtaz, H. (2021). The macroeconomic cost of climate volatility. Queen Mary University of London Working Paper No. 928.

Almeida, C., Ardison, K., Garcia, R., and Vicente, J. (2017). Nonparametric tail risk, stock returns, and the macroeconomy. Journal of Financial Econometrics, 15(3), 333–376.

Alvarez, N., Cocco, A., and Patel, K. B. (2020). A new framework for assessing climate change risk in financial markets. Chicago Fed Letter, 448(1).

Balvers, R., Du, D., and Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. Journal of Banking and Finance, 77, 18–34.

Bansal, R., Kiku, D., and Ochoa, M. (2021). Price of long run temperature shifts in capital markets. NBER Working Paper No. 22529.

Bansal, R., Kiku, D., and Ochoa, M. (Forthcoming). Climate change and growth risks. In: Climate Change Economics: The Role of Uncertainty and Risk, edited by V.V. Chari and Robert Litterman. Hoboken, NJ: Wiley.

Barro, R.J. (2006). Rare disasters and asset markets in the twentieth century. Quarterly Journal of Economics, 121, 823–866.

Barro, R.J. (2009). Rare disasters, asset prices, and welfare costs. American Economic Review, 99(1), 243–264.

Bergeaud, A., Cette, G. and Lecat, R. (2016). Productivity trends in advanced countries between 1890 and 2012. Review of Income and Wealth, 62(3), 420–444.

Boudoukh, J., Richardson, M., and Whitelaw, R.F. (1998). The best of both worlds. Risk, 11, 64–67.

Cao, M., and Wei, J. (2005). Stock market returns: A note on temperature anomaly. Journal of Banking and Finance, 29(6), 1559-1573.

Campbell, J.Y. (2008). Viewpoint: Estimating the equity premium. Canadian Journal of Economics, 41(1), 1–21.

Chandra, M.V. (2021). Weather effects on stock market returns in the United States. Honors Theses and Capstones No. 585. https://scholars.unh.edu/honors/585.

Chebbi, A., and Hedhli, A. (2020). Revisiting the accuracy of standard VaR methods for risk assessment: Using the Copula-EVT multidimensional approach for stock markets in the MENA region. Quarterly Review of Economics and Finance. DOI: 10.1016/j.qref.2020.09.005.

Chevapatrakul, T., Xu, Z., and Yao, K. (2019). The impact of tail risk on stock market returns: The role of market sentiment. International Review of Economics and Finance, 59(C), 289–301.

Clark, T.D., and West, K.D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138, 291–311.

Danielsson, J., and de Vries, C.G. (2000). Value-at-Risk and extreme returns. Annales d'Économie et de Statistique, 60, 239–270.

Dargiri, M.N., Shamsabadi, H.A., Thim, C.K., Rasiah, D., and Sayedy, B. (2013). Value-at-risk and Conditional Value-at-risk assessment and accuracy compliance in dynamic of Malaysian 8ndustries. Journal of Applied Sciences, 13: 974-983.

De Nicolò, G., and Lucchetta, M. (2016). Forecasting tail risks. Journal of Applied Econometrics, 32(1), 159–170.

Diebold, F.X., and Mariano, R.S. (1995). Comparing predictive accuracy. Journal of Business and Economics Statistics, 13, 253−263.

Donadelli, M., Jüppner, M., Paradiso, A., and Schlag, C. (2021a). Computing macro-effects and welfare costs of temperature volatility: A structural approach. Computational Economics, 58, 347–394.

Donadelli, M., Jüppner, M., Riedel, M., and Schlag, C. (2017). Temperature shocks and welfare costs. Journal of Economic Dynamics and Control, 82, 331–355.

Donadelli, M., Jüppner, M., and Vergalli, S. (2021b). Temperature variability and the macroeconomy: A world tour. Environmental and Resource Economics. DOI: `https://doi.org/10.1007/s10640-021-00579-5`.

Elliott, G., Komunjer I. and Timmermann, A. (2005). Estimation and testing of forecast rationality under flexible loss. Review of Economic Studies, 72, 1107–1125.

Elliott, G., Komunjer, I. and Timmermann, A. (2008). Biases in macroeconomic forecasts: Irrationality or asymmetric loss? Journal of the European Economic Association, 6, 122–157.

Engle, R.F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. Review of Financial Studies, 33(3), 1184–1216.

Engle, R.F. and Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk by regression quantiles. Journal of Business and Statistics, 22(4), 367–381.

Floros, C. (2011). On the relationship between weather and stock market returns. Studies in Economics and Finance, 28(1), 5-13.

Giglio, S., Kelly, B., and Stroebel, J. (2021). Climate finance. Annual Review of Financial Economics, 13, 15–36.

Gkillas, K., Konstantatos, C., Tsagkanos, A., and Siriopoulos, C. (2021). Do economic news releases affect tail risk? Evidence from an emerging market. Finance Research Letters, 40, 101727.

Gupta, R., Sheng, X., Pierdzioch, C., and Ji, Q. (2021). Disaggregated oil shocks and stock-market tail risks: Evidence from a panel of 48 Economies. Research in International Business and Finance, 58, 101515.

Harvey, D., Leybourne, S., and Newbold, P. (1997). Testing the equality of prediction mean squared errors. International Journal of Forecasting, 13, 281-291.

He, J., and Ma, X. (2021). Extreme temperatures and firm-level stock returns. International Journal of Environmental Research and Public Health, 18(4), 2004.

Hollstein, F., Nguyen, D.B.B., Prokopczuk, M., and Wese Simen, C. (2019). International tail risk and world fear. Journal of International Money and Finance, 93, 244-259.

Hou, J., Shi, W., and Sun, J. (2019). Stock Returns, weather, and air conditioning. PloS One, 14(7), e0219439.

Jacobsen, B., and Marquering, W. (2008). Is it the weather?. Journal of Banking and Finance, 32(4), 526-540.

Karl, T. R., Melillo, J. M., Peterson, T. C., and Hassol, S. J. (Eds.). (2009). Global climate change impacts in the United States. Cambridge University Press.

Kastner, G., and Frühwirth-Schnatter, S. (2014). Ancillarity-sufficiency interweaving strategy (ASIS) for boosting MCMC estimation of stochastic volatility models. Computational Statistics and Data Analysis, 76: 408-423.

Kelly, B., and Jiang, H. (2014). Tail risk and asset prices. Review of Financial Studies, 27(10), 2841–2871.

Knowlton, K., Rotkin-Ellman, M., Geballe, L., Max, W., and Solomon, G. M. (2011). Six climate change-related events in the United States accounted for about $14 billion in lost lives and health costs. Health Affairs, 30(11), 2167-2176.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347–370.

Li, X-M., and Rose, L.C. (2009). The tail risk of emerging stock markets. Emerging Markets Review, 10, 242–256.

Lu, J., and Chou, R. K. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. Journal of Empirical Finance, 19(1), 79-93.

Luber, G., and McGeehin, M. (2008). Climate change and extreme heat events. American Journal of Preventive Medicine, 35(5), 429-435.

Makkonen, A., Vallsöm, D., Uddin, G.S., Rahman, M.L., and Haddad, M.F.C. (2021). The effect of temperature anomaly and macroeconomic fundamentals on agricultural commodity futures returns. Energy Economics, 100, 105377.

McNeil, A. J., and Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. Journal of Empirical Finance, 7(3-4), 271-300. doi:10.1016/s0927-5398(00)00012-8

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347-370.

Piard, F. (2013). Seasonal patterns in stock markets: 319 years of evidence. Retrieved from `https://seekingalpha.com/article/1183461-seasonal-patterns-in-stock-markets-319-`

Peillex, J., El Ouadghiri, I., Gomes, M., and Jaballah, J. (2021). Extreme heat and stock market activity. Ecological Economics, 179, 106810. doi:10.1016/j.ecolecon.2020.106810

Pindyck, R.S. (2012). Uncertain outcomes and climate change policy. Journal of Environmental Economics and Management 63 (2012) 289-303.

Rietz, T. (1988). The equity risk premium: A solution. Journal of Monetary Economics, 22, 117–131.

Salisu, A.A., Gupta, R., and Ji, Q. (2022a). Forecasting oil price over 150 Years: The role of tail risks. Resources Policy, 75, 102508.

Salisu, A.A., Gupta, R., and Ogbonna, A.E. (Forthcoming a). Tail risks and forecastability of stock returns of advanced economies: Evidence from Centuries of Data. European Journal of Finance.

Salisu, A.A., Pierdzioch, C., and Gupta, R. (2021). Geopolitical risk and forecastability of tail risk in the oil market: Evidence from over a century of monthly data. Energy, 235, 121333.

Salisu, A.A., Pierdzioch, C., and Gupta, R. (2022b). Oil tail risks and the forecastability of the realized variance of oil-price: Evidence from over 150 years of data. Finance Research Letters, 46 (Part B), 102378.

Salisu, A.A., Pierdzioch, C., and Gupta, R. (2022c). Predictability of tail risks of Canada and the U.S. over a century: The role of spillovers and oil tail risks. North American Journal of Economics and Finance, 59, 101620.

Salisu, A.A., Pierdzioch, C., Gupta, R., and Gabauer, D. (Forthcoming b). 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. International Review of Financial Analysis.

Sim, N., and Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking and Finance, 55, 1–8.

Stahle, D. W., Cook, E. R., Cleaveland, M. K., Therrell, M. D., Meko, D. M., Grissino, Mayer, H. D., Watson E, Luckman BH (2000). Tree-ring data document 16th century megadrought over North America. Eos, Transactions of the American Geophysical Union 81(12):212, 125

Stahle, D. W., Fye, F. K., Cook, E. R., and Griffin, R. D. (2007). Tree-ring reconstructed megadroughts over North America since AD 1300. Climatic change, 83(1), 133-149.

Starrs, S. (2013). American economic power hasn't declined-It globalized! Summoning the data and taking globalization seriously. International studies quarterly, 57(4), 817-830.

Table 1: CAViaR Results (S&P500; Stock Log-Returns)

Specification	SAV		ASY		GARCH		ADAPTIVE	
VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR	1% VaR	5% VaR
β_1	-0.0463	0.3804	0.1683	0.5178	0.9205	2.6242	1.0211	1.2532
Standard error	0.1846	0.1868	0.3749	0.1836	3.3938	0.9514	0.2603	0.0405
p-value	0.4009	0.0209	0.3267	0.0024	0.3931	0.0029	0.0000	0.0000
β_2	0.9266	0.8701	0.8642	0.8266	0.8167	0.8258		
Standard error	0.0305	0.0508	0.075	0.0524	0.0385	0.0262		
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
β_3	0.359	0.1736	0.3573	0.0656	1.6795	0.3015		
Standard error	0.1366	0.0598	0.3118	0.0542	2.3037	0.186		
p-value	0.0043	0.0019	0.1259	0.1129	0.233	0.0525		
β_4			0.6145	0.3372				
Standard error			0.442	0.0888				
p-value			0.0822	0.0001				
RQ	175.8546	583.4339	172.795	559.6213	174.2238	579.5742	204.8051	612.8262
Hits in-sample (%)	1.0526	5.0000	0.9649	4.9123	0.9649	5.0000	1.3158	4.9123
Hits out-of-sample (%)	1.3158	3.6842	1.0526	4.2105	1.3158	3.6842	0.7895	5.0000
DQ in-sample (p-values)	0.9795	0.0039	0.1026	0.8978	0.9849	0.1179	0.0000	0.0106
DQ out-of-sample (p-values)	0.9805	0.8181	0.9994	0.9515	0.9875	0.7488	0.3692	0.4815

Note: SAV = Symmetric Absolute Value; ASY = Asymmetric slope; GARCH = Indirect GARCH; ADAPT = Adaptive. In order to identify the "optimal" specification for each VaR, we consider three criteria: (i) %Hits; (ii) DQ test; and (iii) RQ statistic. For the "optimal" specification, the %Hits should be close to 1% for 1% VaR and 5% for 5% VaR, the DQ test statistic should be insignificant, and the the RQ loss function should be minimized (i.e., a smaller RQ statistic is better). We assume that the DQ test takes prominence over the %Hits and the RQ statistics. In cases where more than one tail risk is statistically insignificant in terms of the DQ test, we consider both the %Hits and the RQ statistics to identify the specification with the best fit.

Table 2: Baseline Forecasting Results

Panel A: RMSFE ratio $- TR_1$

Model	h=1	h=3	h=6
GT	0.9987	0.9990	1.0001
GARCH-1	0.9998	1.0010	1.0013
GT and GARCH-1	0.9989	1.0000	1.0005
GARCH-2	1.0003	1.0010	1.0001
GT and GARCH-2	0.9990	0.9998	0.9999

Panel B: RMSFE ratio $- TR_5$

Model	h=1	h=3	h=6
GT	0.9988	0.9990	1.0000
GARCH-1	0.9997	1.0004	1.0007
GT and GARCH-1	0.9988	0.9995	1.0000
GARCH-2	1.0001	1.0003	0.9997
GT and GARCH-2	0.9989	0.9992	0.9995

Panel C: Clark-West Test $- TR_1$

Model	h=1	h=3	h=6
GT	0.7778	0.6244	0.1707
GARCH-1	0.2494	0.0449	0.0811
GT and GARCH-1	0.4313	0.0954	0.1020
GARCH-2	0.0555	0.0475	0.2307
GT and GARCH-2	0.3066	0.0986	0.1491

Panel D: Clark-West Test $- TR_5$

Model	h=1	h=3	h=6
GT	0.7764	0.7002	0.2668
GARCH-1	0.4047	0.1096	0.1752
GT and GARCH-1	0.5347	0.2422	0.2321
GARCH-2	0.1186	0.1585	0.4571
GT and GARCH-2	0.4355	0.2952	0.3342

Panel E: Diebold-Mariano test $- TR_1$

Model	h=1	h=3	h=6
GT	0.8211	0.7475	0.4676
GARCH-1	0.6128	0.3158	0.3027
GT and GARCH-1	0.7390	0.5013	0.4219
GARCH-2	0.4132	0.3519	0.4865
GT and GARCH-2	0.6925	0.5209	0.5098

Panel F: Diebold-Mariano test $- TR_5$

Model / window	h=1	h=3	h=6
GT	0.8201	0.7888	0.4937
GARCH-1	0.7169	0.3876	0.3442
GT and GARCH-1	0.7830	0.6089	0.4997
GARCH-2	0.4502	0.4409	0.5967
GT and GARCH-2	0.7283	0.6434	0.6114

Note: Panels A and B depict the ratio of the root-mean-squared-forecasting errors (RMSFEs) as computed as the ratio of the RMSFE of a benchmark model and a rival model. A ratio that larger than unity indicates that the rival model has a better forecasting performance than the benchmark model. Panels C and D depict results (p-values; based on robust standard errors) of the Clark-West test for an equal mean-squared prediction error (MSPE). The alternative hypothesis is that the rival model has a smaller MSPE than the benchmark model. Panels E and F depict the results (p-values; based on robust standard errors) of the (modified) Diebold-Mariano test. The alternative hypothesis is that the forecasts from the rival model are more accurate than the forecasts from the benchmark model (one-sided test). All panels: The autoregressive model is the benchmark model and the rival model includes the variables displayed in the first column as additional predictors. Forecasts are computed using a recursive estimation window. The training period used to initialize the estimations is ten years.

Figure 1: Results for the Quantiles-on-Quantiles Model

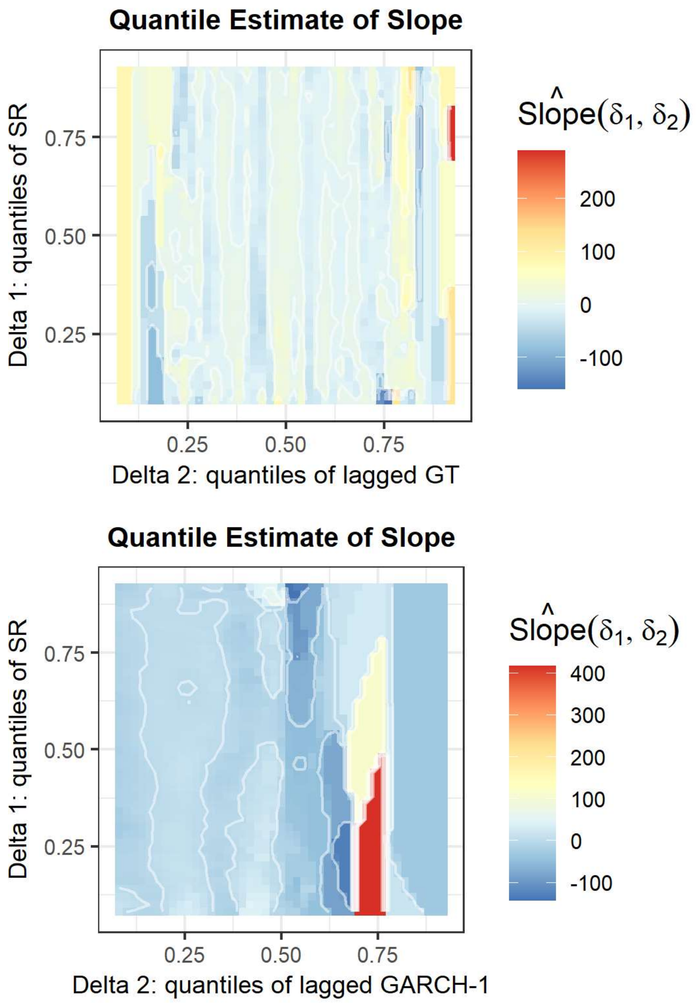


Figure 2: Estimated Tail-Risk Time Series

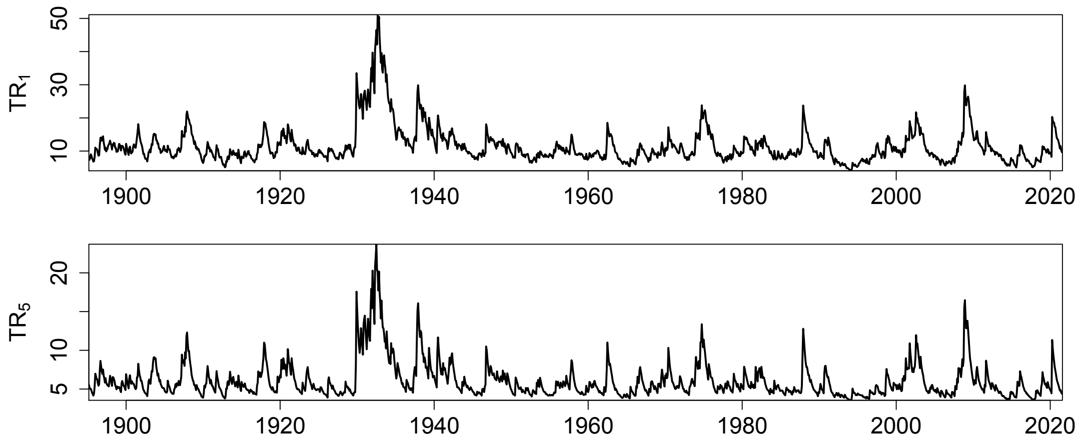
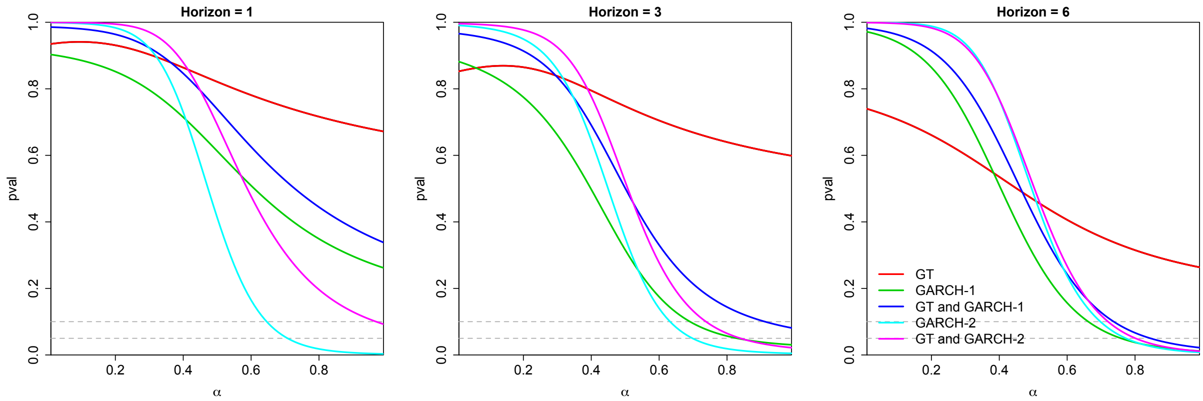
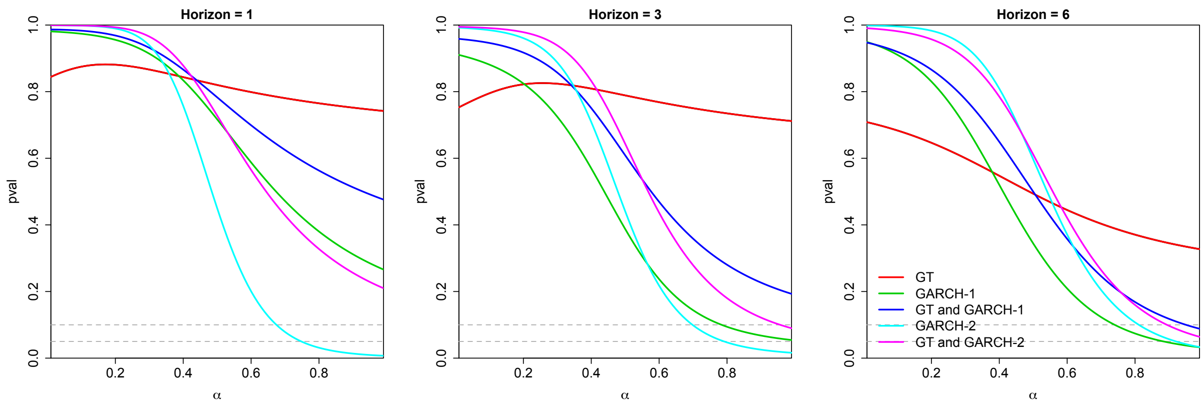


Figure 3: Results for an Asymmetric Loss Function

Panel A: TR_1

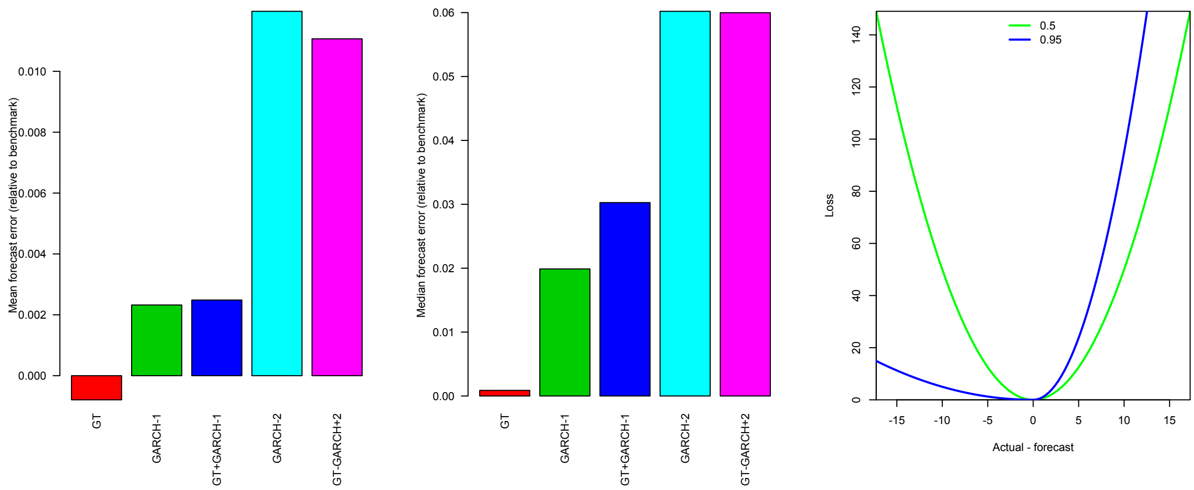


Panel B: TR_5



Note: Results (p-values) of the modified Diebold-Mariano test as a function of the asymmetry parameter. The training period used to initialize the recursive estimation scheme is ten years. Temperature uncertainty is measured by means of GARCH models.

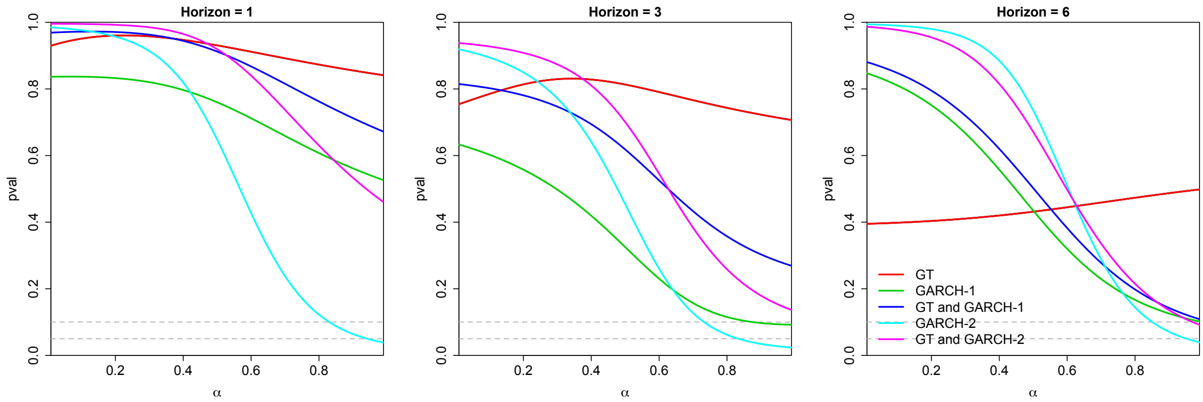
Figure 4: Example



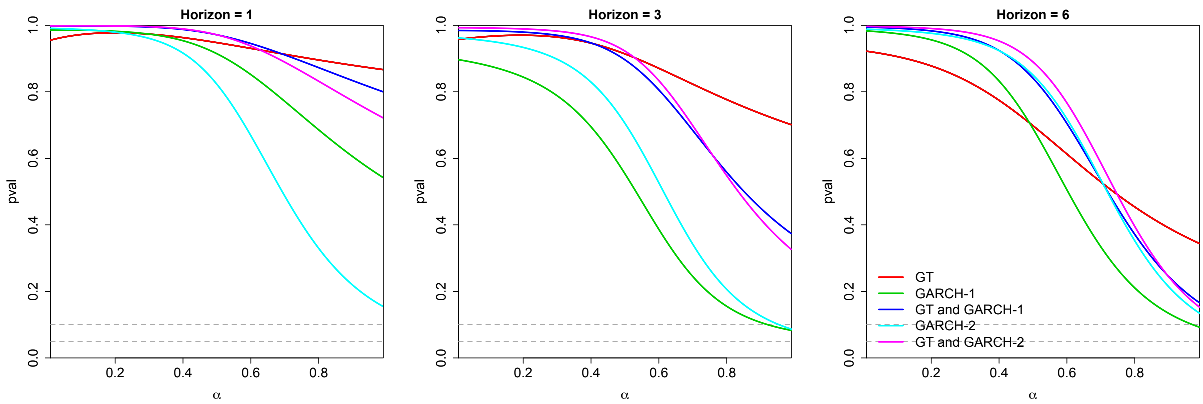
Note: The left-hand (middle) panel plots the mean (median) of the forecast error produced by the models given on the horizontal axis relative to the forecast error of the benchmark model (without climate predictors). The example uses data for TR_1, a training period of ten years, and a forecast horizon of $h = 3$. The right-hand panel plots two examples of the loss function, where the shape parameter takes on the values $\alpha = 0.5$ (symmetric case) an $\alpha = 0.95$ (asymmetric case).

Figure 5: Results for a Rolling-Estimation Window

Panel A: TR_1



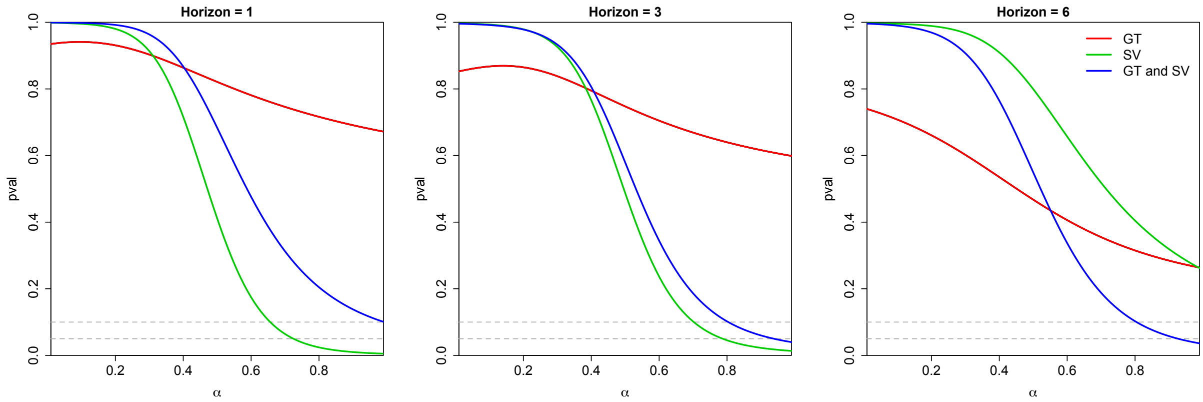
Panel B: TR_5



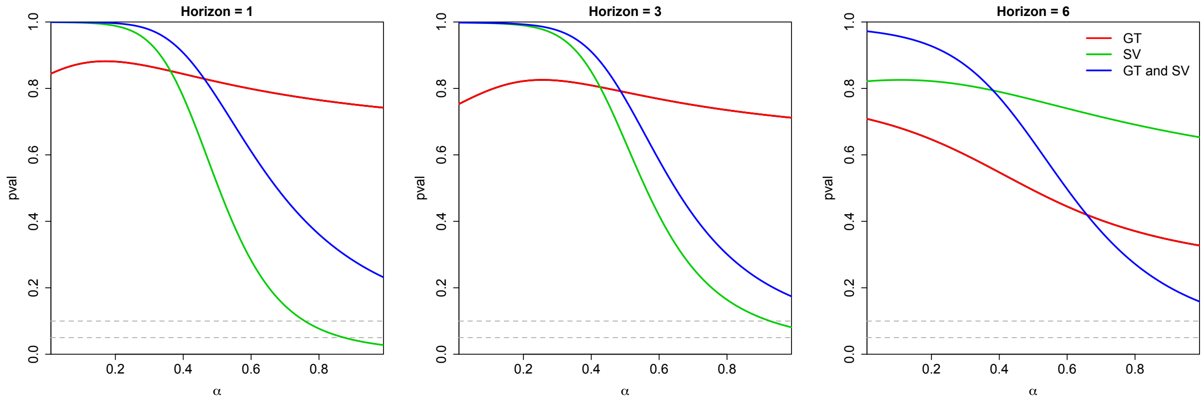
Note: Results (p-values) of the modified Diebold-Mariano test as a function of the asymmetry parameter. The rolling-estimation window has a length of ten dears. Temperature uncertainty is measured by means of GARCH models.

Figure 6: Results for a Stochastic Volatility Model

Panel A: TR_1



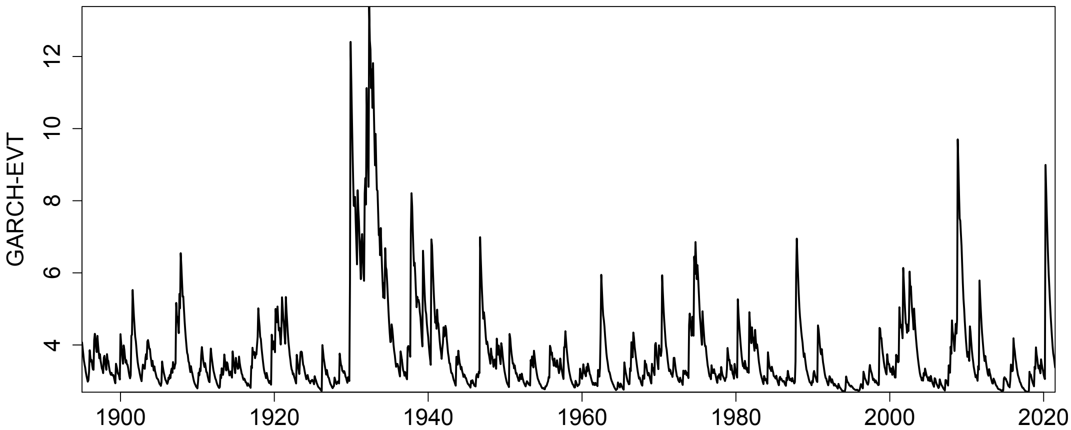
Panel B: TR_5



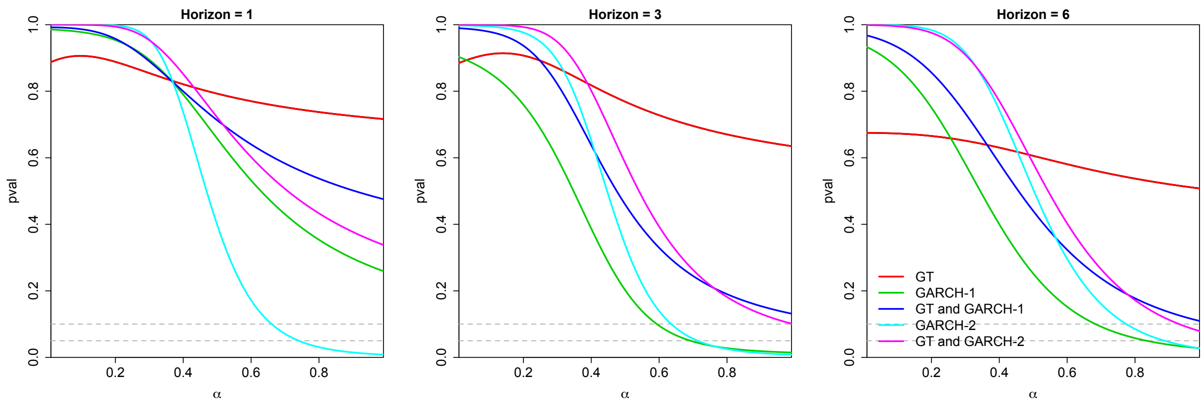
Note: Results (p-values) of the modified Diebold-Mariano test as a function of the asymmetry parameter. The training period used to initialize the recursive estimation scheme is ten years. Temperature uncertainty is measured by means of a stochastic-volatility (SV) model.

Figure 7: Results for the GARCH-EVT Model

Panel A: Estimated tail risk



Panel B: Diebold-Mariano test



Note: Results (Panel B; p-values) of the modified Diebold-Mariano test as a function of the asymmetry parameter. The training period used to initialize the recursive estimation scheme is ten years. Temperature uncertainty is measured by means of GARCH models.