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Book

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Forecasting Stock Returns Volatility of the G7 Over Centuries: The Role of Climate Risks

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Abstract

We analyze whether changes in temperature anomalies, and its second, third, and fourth moments carry valuable information in forecasting historical stock returns volatility of Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (US), i.e., the G7 countries, after controlling for leverage, skewness and (excess) kurtosis of stock price fluctuations. Using centuries of monthly data, covering the period 1915–2024 for Canada and Italy, 1898–2024 for France, 1870–2024 for Germany, 1914–2024 for Japan, 1693–2024 for the UK, and 1791–2024 for the US, the results show that stock market moments matter more than climate risks for accurately forecasting stock returns volatility. Extended analyses confirm that climate risks are already captured by the moments of stock returns. We discuss the implications of our findings for investment decisions and economic policy.

JEL Classifications: C22; C32; C53; G10; G17; Q54

Keywords: Stock market; Volatility; Forecasting; Moments; Climate risks; G7 countries

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1 Introduction

Climate change-related extreme weather conditions constitute a large aggregate risk (Del Fava et al., 2024). Climate risks also have been shown theoretically to reduce productivity and/or increase the stochastic depreciation rate of capital in Dynamic Stochastic General Equilibrium (DSGE) models and, thus, can be expected to give rise to adverse impacts on equity valuations (Donadelli et al., 2017, 2021a, 2021b, 2022; Giglio et al., 2021a). In other words, climate risks tend to impact negatively future (aggregate and sectoral) stock returns, as has been shown empirically by Balvers et al. (2017), Choi et al. (2020), Bolton and Kacperczyk (2021), Balcilar et al. (2023), Faccini et al. (2023), Salisu et al. (2023a, 2024), among others.[1]

Building on the first-moment impact of climate risks on stock markets, two recent studies by Bonato et al. (2023) and Wu et al. (2024) have highlighted its role in forecasting stock returns volatility.[2] In the former study, the authors provide evidence of forecastability of US state-level realized stock-market volatility (derived from intraday data) at medium- to long forecasting horizons, while they provide in the latter study results for an emerging market, namely South Africa, and show that climate risks carry out-of-sample predictive information for conditional volatility, especially at longer forecasting horizons.[3]

In this research, we extend this literature by analyzing the role of climate risks in forecasting the second moment of monthly stock returns of the G7 countries, i.e., Canada, France, Germany, Italy, Japan, the UK, and the US, from a historical perspec-

[1] In this regard, a related strand of literature has highlighted comparatively better portfolio performance of green stocks rather than brown stocks in hedging climate risks (see, for example, Engle et al. (2020), Cepni et al. (2022, 2023), Ardia et al. (2023)).

[2] From an in-sample perspective, Penzin et al. (2024) has related climate risks with stock market volatility, conditional on levels of technological changes.

[3] In this context, it is important to mention the works of Chen et al. (2023), Lv and Li (2023), and Lasisi et al. (2024), who show that uncertainty surrounding climate policies can produce forecasting gains in Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type models for aggregate and sectoral stock returns volatility of China, the United Kingdom (UK) and the US.

tive. Specifically, we collected data starting at March, 1915 for Canada and Italy, February, 1898 for France, February, 1870 for Germany, September, 1914 for Japan, March, 1693 for the UK, and October, 1791 for the US, with all the time series of stock returns ending in January, 2024. Besides the availability of the longest possible samples of stock market data to avoid a potential sample-selection-bias, our choice of the aforementioned stock markets was primarily motivated by their importance to the global economy, because they represent nearly two-thirds of global net wealth and nearly half of the world output (Das et al., 2019; Salisu et al., 2023b). Hence, analyzing the link between climate risks and stock market volatility for the G7 countries is of pivotal importance from the perspective of the stability to the world financial system, and its associated investment and policy implications. Furthermore, by studying such long spans of data, we were able to capture the fact that climate change is a slow-moving process and its effects have tended to aggravate over time as economies have become more industrialized.

In order to achieve our objective, we proceeded in two steps. In the first step, we used the Autoregressive Conditional Density (ACD) model (Hansen, 1994) to estimate the conditional volatility of the G7 stock returns, which we aim to forecast. The advantage of the ACD model is that it also estimates the skewness (depicting asymmetry) and the (excess) kurtosis (capturing outliers) series. This is important because skewness and kurtosis, along with leverage (i.e., a time series of negative stock returns), have been shown to play important roles in forecasting stock market volatility (Mei et al., 2017; Zhang et al., 2021; Bonato et al., 2023). Hence, we use in our predictive framework leverage, skewness, and (excess) kurtosis as controls to avoid a potential omitted-variables-bias, along with the measures of climate risks. As far as measures of climate risks are concerned, besides the year-on-year changes in country-specific temperature anomalies, we used the ACD model again to derive the associated measures of conditional volatility, skewness, and (excess) kurtosis. In the process, unlike the above-mentioned literature that models climate risks with the first and second moments of changes in temperature anomalies, we were able to capture asymmetric and extreme climate-related risks as well through the third and fourth moments of the deviation of temperature from its long-term trend.

Once we had obtained the moments of both stock returns and changes in temperature anomalies, in the second step, we utilized a (conditional mean-based) predictive regression model to check for the forecasting ability of the four climate risks predictors for the stock market volatility of the G7 countries, over and above the role of leverage, skewness, and (excess) kurtosis of the corresponding stock returns. In addition, we utilized a quantile regression model (originally developed by Koenker and Bassett (1978)) for our forecasting exercise, which renders it possible to investigate the predictive ability of the predictors in forecasting the entire conditional distribution of stock market volatility. Studying the entire conditional distribution is important because the conditional mean may “hide” interesting characteristics of the predictand (Meligkotsidou et al., 2014), and can lead to poor predictive performance, with the predictors possibly being valuable for forecasting certain parts of the conditional distribution of stock market volatility. Furthermore, the quantile regression model retains the simple structure of a linear framework for any given quantile of volatility but, simultaneously, renders it possible to consider an element of nonlinearity because the coefficients of the predictive model are allowed to vary across the different quantiles of the conditional distribution of stock market volatility. This is important especially in our context because we analyzed centuries of data, wherein the relationship between the predictand and the predictors may have been disrupted by regime changes (see,, for example, the discussions in Balcilar et al. (2023), and Salisu et al. (2023a, b)).

A forecasting experiment involving the role of climate-related physical risks, which have become more prevalent in terms of magnitude, severity, and frequency, with this trend expected to continue in the future (Mendelsohn et al., 2012; Stott, 2016), on the volatility of the G7 stock markets is indeed a pertinent issue. Accurate forecasts of stock market volatility carry widespread investment implications, being an input in portfolio models, derivative pricing, and risk management (Poon and Granger, 2003; Rapach et al., 2008). In addition, stock market volatility, as was evident during the Global Financial Crisis of 2007–2009 and the recent COVID-19 pandemic, can impinge back on the economy as a whole via its effect on real economic activity and public confidence (Jurado et al., 2015; Ludvigson et al., 2021). Naturally, forecasts of stock market volatility can serve as a measure of the vulnerability of the overall financial system and the whole economy and, thereby, help policymakers design appropriate preventive policies. Finally, our research also carries academic value in that we are postulate the hypothesis that climate risks can predict stock market volatility and, in turn, check for its validity in the context of an out-of-sample forecasting exercise, which is well-established as a stronger test of predictability than in-sample analyses (Campbell, 2008).

At this stage, given our testable empirical hypothesis, it makes perfect sense to outline a theoretical link through which climate risks, serving as a proxy for rare disaster events (Bansal et al., 2021, forthcoming; Giglio et al., 2021b), are expected to drive stock market volatility. Rietz (1988), and later Barro (2006, 2009), have proposed models of rare disasters to explain the equity premium puzzle, which was initially identified by Mehra and Prescott (1985). More recently, Wachter (2013) and Tsai and Wachter (2015) have extended this line of research by developing theoretical frameworks in which aggregate consumption follows a normal distribution with low volatility most of the time, but a far out-in-the-left-tail realization of consumption can occur with some probability, creating disaster risk. Disaster risk not only substantially raises the equity premium, but the time-variation in its probability is reflected in stock market volatility. In other words, a well-established theoretical channel exists that warrants a detailed empirical analysis of the link between extreme-climate events-produced disaster risks and stock market volatility of the G7 countries. In light of this, we lay out in our research empirical results that shed light on the climate-risks-stock-market-volatility nexus from a forecasting perspective for the first time covering multiple centuries of data.

We organize the rest of this research as follows. In Section 2, we provide a description of the data we use in our study, while we outline in Section 3 the ACD model used to derive the moments of our data, and the linear and quantiles-based forecasting models. In Section 4, we present our empirical results. In Section 5, we conclude.

2 Data

Our dataset consists of the monthly aggregate stock market indexes of the G7 countries, namely the S&P TSX 300 Composite Index for Canada, the CAC All-Tradable Index for France, the CDAX Composite Index for Germany, the Banca Commerciale Italiana Index for Italy, the Nikkei 225 Index for Japan, the FTSE All Share Index for the UK and the S&P500 Index for the US. For each stock index, we compute log-returns (in percentages) as the first-difference of the logs of the index, multiplied by 100. We obtained the data on the stock indexes Global Financial Data.[4]

As far as the corresponding monthly temperature anomalies (relative to a historical mean over the period 1991–2020) data are concerned, barring the UK and the US, we obtained the data from the website of the National Oceanic and Atmospheric Administration (NOAA).[5] Because the NOAA data on temperature anomalies only start from 1850:01, we rely on data from the Met Office Hadley Centre for relevant data for the UK,[6] and Berkeley Earth[7] for the US until 2016:12, [8], and then updated up to and including 2024:01using comparable values of temperature anomalies from the NOAA.[9] Once we obtained the temperature anomalies, we computed year-on-year changes of the

[4] https://globalfinancialdata.com/.

[5] See: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series, wherein we need to specify the respective coordinates, i.e., latitude and longitude.

[6] https://www.metoffice.gov.uk/hadobs/hadcet/data/download.html.

[7] https://berkeleyearth.org/data/.

[8] https://berkeley-earth-temperature.s3.us-west-1.amazonaws.com/Regional/TAVG/united-states-TAVG-Trend.txt.

[9] https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/national/time-series.

monthly variables to ensure that we removed any seasonal patterns.

Based on the availability of stock market data, the coverage is heterogenous with Canada and Italy starting in 1915:03, France in 1898:02, Germany in 1870:02, Japan in 1914:09, the UK in 1693:03, and the US in 1791:10, but all the data end in 2024:01, corresponding to the availability of the latest data at the time of conducting the estimations.

3 Methods

We first lay out the ACD model that we used to extract the higher-order moments for both the stock returns and changes in temperature anomalies. We then present the forecasting models that we used to for forecasting the conditional volatility (VOL) of the G7 stock returns, based on the information contained in leverage (LEV), skewness ($SKEW$) and (excess) kurtosis ($KURT$) of stock returns, and year-on-year changes in temperature anomalies ($CR1$), its conditional volatility ($CR2$), skewness ($CR3$), and (excess) kurtosis ($CR4$), with the climate risks considered both individually and together.

3.1 Measuring Moments

We used the ACD model to derive the conditional higher-order moments (conditional volatility, skewness, and (excess) kurtosis) of G7 stock market log-returns, as well as for the year-on-year changes in temperature anomalies.[10] Denoting the log-returns of a particular stock market index or the year-on-year changes in temperature anomalies by y_t, the mean and variance equations of the Autoregressive Moving Average (ARMA)-GARCH model are given by:

[10]We used the R language and environment for statistical computing (R Core Team, 2023) for all our empirical analyses. For the estimation of the ACD model, we rely on the R add-on package "racd" (Ghalanos, 2014).

$$y_t = c + \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{j=1}^{q} \eta_j \varepsilon_{t-j} \quad , \quad \varepsilon_t = \sigma_t z_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} a_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where $z_t \sim D(0, 1, \theta_t, \tau_t)$; ε_t and z_t denote the residuals and white noise disturbances (with unit variance), σ_t^2 denotes the conditional variance, and ε_{t-i}^2 denotes the past innovation to the variance. Three conditions are required to ensure positivity ($\omega > 0$, $\alpha_1 \leq 0$ and $\beta_1 \leq 0$).

The ARMA-GARCH model is enhanced with complementary parameters relating dynamic conditional skewness and conditional (excess) kurtosis of a distribution D as follows:

$$\theta_t = \Phi(\theta_t) \tag{3}$$

$$\tau_t = \Phi(\tau_t) \tag{4}$$

Modelling skewness and kurtosis requires the application of the distributional parameters θ_t and τ_t. These parameters are restricted within the lower (L) and upper (U) bounds as follows:

$$\Phi(\theta_t) = L_{\theta_t} + \frac{(U_{\theta_t} - L_{\theta_t})}{1 + e^{-\theta_t}} \tag{5}$$

$$\Phi(\tau_t) = L_{\tau_t} + \frac{(U_{\tau_t} - L_{\tau_t})}{1 + e^{-\tau_t}} \tag{6}$$

The skew parameter, θ_t, reflects the asymmetry of the distribution of stock market returns or year-on-year changes in temperature anomalies. The shape parameter, τ_t, reflects the kurtosis of the tails of each of these two variables, and L and U represent the lower and upper bounds of the two distributional parameters, θ_t and τ_t. As for $\Phi(.)$, it signifies a transformation function.

Like Hansen (1994), we allow the parameters of skew and shape to evolve over time. Accordingly, the first-order quadratic-type evolution of these parameters is given by:

$$\theta_t = \alpha_0 + \alpha_1 z_{t-1} + \alpha_2 z_{t-1}^2 + c_1 \theta_{t-1} \tag{7}$$

$$\tau_t = b_0 + b_1 z_{t-1} + b2 z_{t-1}^2 + d_1 \tau_{t-1} \tag{8}$$

In this regard, the conditional volatility, conditional skewness, and conditional (excess) kurtosis are estimated under the assumption of normal inverse Gaussian innovations, which is suitable for achieving a reasonable modellng (see, among others, He and Hamori (2021), Ahmed et al. (2024)).

3.2 Forecasting Models

In order to conduct our forecasting experiment, we used variants of the following forecasting model:

$$VOL_{t+h} = \beta_0 + \beta_1 VOL_t + \beta_2 LEV_t + \beta_3 SKEW_t + \beta_4 KURT_t + \beta_5 CR_t + u_{t+h}, \tag{9}$$

which we estimated by the ordinary-least-squares (OLS) technique, $\beta_j, j = 0,..,5$ are coefficients to be estimated, u_{t+h} denotes a disturbance term, and VOL_{t+h} is the average stock market volatility over the forecast horizon, h. We analyzed five short, intermediate, and long forecasting horizons by setting $h = 1, 3, 6, 9, 12$. The stock-market predictors were the period-t stock market volatility (VOL_t), LEV_t, $SKEW_t$, and $KURT_t$. In addition, we included, in an extended forecasting model, one or more of the climate risks, CR_t

(where β_5 is an appropriately dimensioned vector of coefficients in case we include more than one climate risk in the forecasting model).[11]

In order to inspect whether the climate risks contribute to forecast accuracy, we set up our forecasting experiment using a recursive and a rolling estimation window. When we studied a recursive estimation window, we used the first 25% of a dataset to initialize the estimations, and then expanded the estimation window step by step until we reached the end of the sample period. Similarly, when using a rolling estimation window, we used the first 25% of a dataset for initialization, then added one observation at the end of the estimation window and dropped one observation at the beginning of the estimation window, and continued in this way until we reached the end of the sample period. For every recursive and rolling estimation window, we computed out-of-sample forecasts of stock market volatility for the five different forecast horizons under study.

We evaluated the resulting sequences of out-of-sample forecasts resulting from the recursive and the rolling estimations in three different ways. First, we computed the root-mean-squared forecast error (RMSFE) for all forecasting models, where we expressed the RMSFE in terms of a ratio by comparing the RMSFE of a benchmark and a rival model. A RMSFE ratio larger than unity, thereby, signals that the rival model produced a lower RMSFE than the benchmark model. The rival model included one or more climate risks as predictors, while the benchmark model included only stock-market-related predictors. Second, we took analogous steps to compute the ratio of the mean absolute forecast error (MAFE) of a benchmark and a rival model.

As an extension, we estimated the forecasting model given in Equation (9) as a quantile-regression model. Such an extension is useful to answer the question whether climate risks have differential effects across different quantiles of the conditional distribution of conditional stock market volatility. The quantile-regression model is given by

[11] Moreover, we used, as an extension, an optimal predictor selection algorithm (which we shall describe in more detail in Section 4.3) to let the data decide on which of the climate predictors to include in the optimal forecasting model.

the following equation:

$$\mathbf{b_q} = \arg\min \sum_{t}^{T} \rho_q \left(VOL_{t+h} - \beta_0 - \beta_1 VOL_t - \beta_2 LEV_t - \beta_3 SKEW_t - \beta_4 KURT_t - \beta_5 CR_t \right), \tag{10}$$

where q denotes the quantile being studied, $\mathbf{b_q}$ denotes the quantile-dependent vector of coefficients, and the function ρ_q, denotes the usual check function, defined as $\rho_q = q u_{t+h}$ for $u_{t+h} > 0$, and $\rho_q = (q-1) u_{t+h}$ for $u_{t+h} < 0$. We studied the following quantiles: $q = \{0.1, 0.25, 0.5, 0.75, 0.9\}$, using the same recursive and rolling estimation windows that we used to estimate the OLS model given in Equation (9). Hence, the time index in Equation (10) covers the relevant estimation window.[12]

We evaluated the resulting out-of-sample forecasts for the different quantiles using the check function. Hence, we assumed that the check function represents the loss function a forecaster uses to estimate a forecasting model as well as to evaluate, given a quantile, the resulting forecast errors. We computed in this way the average forecast error for every forecasting model and quantile, and scaled the resulting numbers by forming their ratio for a benchmark and a rival model.

4 Empirical Results

4.1 Baseline Results

We report in Table 1 RMSFE ratios as computed by estimating Equation 9 by means of a recursive estimation window. We observe that the forecasts that we obtained from estimating the AR-MOM model are more accurate in terms of the RMSFE criterion than the forecasts that we computed by means of the corresponding AR model for all seven countries and all five forecast horizons, where the RMSFE ratios decrease as the forecast horizon gets longer (with the results for Germany being an exception). In sharp contrast,

[12]We use the R add-on package "quantreg" (Koenker, 2023) to estimate the quantile-regression models.

when we compare the AR-MOM model with the variants of the AR-MOM-CR model, we observe that the latter performs worse than the AR-MOM model in terms of the RMSFE criterion in most cases, and performs better than the AR-MOM model by a tiny margin only in a few cases. Hence, the punchline is that stock market moments rather than the climate risks matter for out-of-sample predictive accuracy.

– Table 1 about here. –

The MAFE results that we report in Table 2, again for a recursive estimation window, corroborate that the result that stock market moments matter while climate risks do not. As in the case of the RMSFE ratios, we found that the MAFE ratios tend to exceed unity when we compare the AR benchmark model with the AER-MOM rival model. An exception in this regard are the results for Italy. For Canada, we found that CR2 and CR3 contribute some moderate predictive value at the intermediate forecast horizons. The general result, however, is that climate risks do not contribute much, if anything, to out-of-sample forecasting performance in terms of the MAFE criterion relative to stock market moments.

– Table 2 about here. –

Next, we turn to the RMSFE ratios we obtained for a rolling estimation window, as reported in in Table 3. The results demonstrate that the AR-MOM model performs better than the AR benchmark model for Canada, France, Germany, Italy, and Japan. Stock market moments did not improve out-of-sample forecasting performance when we studied data for the United Kingdom and the United States. Importantly, there is hardly any evidence that the climate risks go beyond stock market moments in terms of out-of-sample forecasting accuracy.

– Table 3 about here. –

4.2 Quantile-Regression Results

We summarize the results of the quantile-regression-based analyses in Figure 1 for a recursive estimation window and in Figure 2 for a rolling estimation window. In these figures, we plot the check-function ratios, which we calculated using out-of-sample forecasts, as a function of the quantiles, where we focus on a comparison of the AR vs. AR-MOM models and the AR-MOM vs. AR-MOM-CR models (the model that features all four climate risks) for better readability of the figures.

– Figures 1 and 2 about here. –

The general message of the quantile-regression-based analyses is in line with the main result of the OLS analyses. The AR-MOM model performs better than the AR model for the overwhelming majority of combinations of countries, forecast horizons, and quantiles. As compared to the AR-MOM model, the AR-MOM-CR model either produces rather small forecasting gains or even performs worse. Hence, we conclude that stock market moments, on balance, matter much more for forecasting accuracy of stock returns volatility than climate risks.

4.3 Extensions

A natural question is whether the contribution of the climate risks to out-of-sample forecasting accuracy became more substantial in the second half of the sample period given that the awareness for climate-related risks can be expected to have increased in general towards the end of the sample period. The RMSFE ratios are reported in Table 4 (recursive estimation window) and in Table 5 (rolling estimation window). As compared to the results reported in Tables 1 and 3, we deleted the first 50% of the out-of-sample forecasts. Again, we found that, on balance, the stock market moments are more important for out-of-sample forecasting accuracy of volatility of the G7 equity market returns than the climate risks. Stock market moments lost in importance relative to our baseline results in the cases of Germany and Italy (the latter mainly in case of a recursive estimation window), but gained in importance in the cases of the United Kingdom and the United States (rolling estimation window).

– Tables 4 and 5 about here. –

It is an arbitrary choice, of course, simply to delete the first 50% of the out-of-sample forecasts. As an alternative specification, we discounted "old" forecast errors using the formula $FE_s \times \gamma^{T-s}$, for $s = T, T-1, T-2, ...$, where FE denotes the forecast error and T denotes the last observation of the sequence of out-of-sample forecasts. We set $\gamma = 0.98$. Hence, more recent forecast errors receive a larger weight as compared to more distant forecast errors. We summarize the results in Table 6 (recursive estimation window) and Table 7 (rolling estimation window). As for the results we obtained based on a recursive estimation window, we found that stock market moments add to forecast accuracy in all countries except Germany. In addition, we found that one of the climate risks, CR4, yielded a noticeable forecasting gains at the longer forecast horizons when we studied the data for Germany, Italy, and Japan. Turning next to the results for the rolling estimation window, we again found strong evidence, for all countries in our sample, that stock market moments add to forecast accuracy beyond the AR benchmark model, while the effect of CR4 on forecasting accuracy was visible only for the Japanese data.

– Tables 6 and 7 about here. –

As a further extension, we used an optimal stepwise predictor selection approach to let the data decide which climate risks to include in the forecasting models (for a textbook exposition, see Chapter 3 of Hastie et al. (2009)). We implemented a forward variant of this algorithm. To this end, we started with the AR-MOM model and estimated by the OLS technique the forecasting models that incorporate only one of the climate risks as an additional predictor. We stored the model for which we obtained the minimum residual sum of squares. Then we started the next round of the algorithm with this model and estimated all models that include two climate risk predictors (the one selected in the first step plus one additional climate risk). Among these models, we chose the model that minimized the residual sum of squares. We continued this process until we reached the forecasting model that features simultaneously all climate risks. Applying the optimal forward stepwise predictor selection algorithm in this way gave us a sequence of forecasting models with increasing complexity. From these sequences of models, we selected the forecasting model that (i) maximized the adjusted R^2 statistic, (ii) minimized the Bayesian Information Criterion (BIC), or (iii) minimized Mallow's CP criterion.[13]

– Tables 8 and 9 about here. –

We summarize the results for the optimal stepwise predictor selection approach in Table 8 (RMSFE ratios) and Table 9 (MAFE ratios). We found that the climate risks either do not or do not contribute much beyond the stock market moments to forecast accuracy. This finding was in line with the results of our other analyses.

4.4 Explaining the Findings

At this stage, it is important to provide a possible explanation for our finding that climate risks relative to the moments of stock returns of the G7 countries do not necessarily add much in terms of forecasting gains associated with corresponding volatilities of these seven advanced economies. We believe that this is likely due to the fact that the climate risks are already reflected in the leverage, skewness, and (excess) kurtosis of the stock returns, as the moments themselves encapuslate the impact of the broader concept of rare disaster events, a part of which is captured by climate risks, on asset market volatility (Gkillas et al., 2019; Bonato et al., 2022; Gupta et al., 2023). This line of reasoning

[13]We utilize the R add-on package "leaps" by Lumley (2020), which is based on Fortran code by Alan Miller, to implement the optimal stepwise predictor selection algorithm.

is, in fact, vindicated by the results from the nonparametric causality-in-quantiles test of Jeong et al. (2012), which being a data-driven nonparametric test, controls for any misspecification due to nonlinearity and structural breaks, while producing predictive information about the entire conditional distribution of the dependent variables.

– Table 10 about here. –

As can be seen from Table 10, after applying the nonparametric causality-in-quantiles test, in general, there is strong evidence of predictability emanating from all the four climate risks-related variables for the entire conditional distributions of leverage, skewness, and (excess) kurtosis of the G7 stock markets. Understandably, it is impossible to draw an one-to-one correspondence to the findings of Bonato et al. (2023) and Wu et al. (2024), due to differences in the underlying econometric methods and sample periods. But, we are inclined to believe that not accounting for moments could tilt the scale in favor of the climate risks variables in forecasting stock market volatility, as reported by Wu et al. (2024) for South Africa, who, in turn, did not incorporate the role of leverage, skewness, and (excess) kurtosis in modeling the process of volatility. At the same time, the favorable results reported by Bonato et al. (2023) for forecasting of US state-level stock market volatility originating from extreme weather impacts, over and above the moments, could be highlighting the fact that regional climate variables tend to have heterogeneous data-generating processes (Gil-Alana et al., 2022), which can get washed out in defining the underlying state of the economy at the aggregate-level (Cepni et al., 2024). Moreover, with the state-level stock prices being a capitalization-weighted index of equities domiciled in a state, the findings could also be depicting industry-specific impacts, as sectors indeed can differ in their sensitivity to climate-change-related risks.

5 Concluding Remarks

In light of the burgeoning literature on "climate finance", our objective in this research was to analyze whether changes in temperature anomalies, and its second, third, and fourth moments carry predictive content for forecasting historical stock returns volatility of the G7 countries spanning centuries of data, once we control for leverage, skewness, and (excess) kurtosis of stock returns. The general message to take home from the main results is that stock market moments matter more thank climate risks for accurately forecasting stock returns volatility, with climate risks being already captured by the moments, as shown by the results of a causality-in-quantiles test. While our results do not rule out that climate risks may have contributed to forecasting accuracy during some time-periods and for some countries and model configurations, our results have shown that, on balance, the role of stock market moments to forecasting accuracy relative to an autoregressive benchmark model is more robust across countries and model configurations and, in the majority of cases, they are also quantitatively relatively important than the incremental contribution of climate risks. A quantiles-based analysis and several variations of the forecasting model does not changed the main empirical observation. Based on our findings, we conclude that, in spite of theoretical predictions, on the practical front, investors and policymakers in the G7 countries should closely track moments rather than physical climate risks when they need to produce forecasts of stock market volatility, when such forecasts perhaps are being utilized as inputs in portfolio allocation and policy decisions.

As part of future analysis, it is interesting to extend our analysis to sector-level data. In this regard, the US would be an obvious choice with such data available back to 1926 at a monthly frequency. More importantly, climate-change risks are typically divided into two main components, namely physical and transition risks. While the former stems from the detrimental impacts of climate-related events, which is what we have studied in our research, the latter arises from the gradual shift toward a low-carbon economy (as reflected, for example, in climate and environmental policies, the strengthening competitiveness of eco-friendly technologies, and an adaptation in consumer preferences), which we have completely ignored. Understandably, both physical and transition risks are an integral part of every conceivable future scenario, albeit with varying degrees or forms of uncertainty. While dealing with transition risks would substantially shorten our sample periods to the turn of this century due to data availability (see, Bua et al. (2024) for a detailed discussion), their importance in driving financial-market moments in both developed and developing economies warrants a detailed investigation in future research.

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Table 1: RMSFE ratios for a recursive estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	1.7928	1.3114	1.1443	1.0810	1.0538
Canada / AR-MOM vs. AR-MOM-CR1	0.9988	0.9982	0.9990	0.9994	0.9996
Canada / AR-MOM vs. AR-MOM-CR2	0.9987	0.9988	0.9981	0.9890	0.9725
Canada / AR-MOM vs. AR-MOM-CR3	0.9992	0.9988	0.9976	0.9960	0.9953
Canada / AR-MOM vs. AR-MOM-CR4	0.9979	0.9968	0.9980	0.9992	1.0000
Canada / AR-MOM vs. AR-MOM-CR	0.9934	0.9912	0.9929	0.9786	0.9596
France / AR vs. AR-MOM	1.7072	1.2598	1.1271	1.0791	1.0615
France / AR-MOM vs. AR-MOM-CR1	1.0003	0.9996	0.9995	0.9995	0.9995
France / AR-MOM vs. AR-MOM-CR2	0.9983	0.9986	0.9980	0.9987	0.9982
France / AR-MOM vs. AR-MOM-CR3	0.9983	0.9983	0.9974	0.9978	0.9974
France / AR-MOM vs. AR-MOM-CR4	0.9984	0.9986	0.9977	0.9981	0.9976
France / AR-MOM vs. AR-MOM-CR	0.9996	0.9981	0.9954	0.9972	0.9960
Germany / AR vs. AR-MOM	1.0186	1.0481	1.0478	1.0546	1.0743
Germany / AR-MOM vs. AR-MOM-CR1	0.9987	0.9994	0.9998	0.9997	0.9995
Germany / AR-MOM vs. AR-MOM-CR2	1.0000	1.0004	1.0020	1.0035	1.0045
Germany / AR-MOM vs. AR-MOM-CR3	1.0001	1.0006	1.0023	1.0037	1.0046
Germany / AR-MOM vs. AR-MOM-CR4	0.9999	0.9998	1.0007	1.0020	1.0034
Germany / AR-MOM vs. AR-MOM-CR	0.9990	0.9998	1.0012	1.0020	1.0030
Italy / AR vs. AR-MOM	1.0619	1.0391	1.0208	1.0144	1.0050
Italy / AR-MOM vs. AR-MOM-CR1	1.0000	0.9996	0.9991	0.9989	0.9981
Italy / AR-MOM vs. AR-MOM-CR2	0.9998	0.9999	0.9997	0.9997	0.9994
Italy / AR-MOM vs. AR-MOM-CR3	0.9997	0.9995	0.9992	0.9992	0.9988
Italy / AR-MOM vs. AR-MOM-CR4	1.0000	0.9969	0.9943	0.9949	0.9917
Italy / AR-MOM vs. AR-MOM-CR	0.9992	0.9938	0.9916	0.9911	0.9867
Japan / AR vs. AR-MOM	1.1088	1.0520	1.0684	1.0668	1.0366
Japan / AR-MOM vs. AR-MOM-CR1	0.9978	0.9945	0.9920	0.9918	0.9942
Japan / AR-MOM vs. AR-MOM-CR2	0.9997	0.9910	0.9907	0.9958	0.9972
Japan / AR-MOM vs. AR-MOM-CR3	0.9989	0.9892	0.9891	0.9938	0.9954
Japan / AR-MOM vs. AR-MOM-CR4	0.9999	1.0032	1.0076	1.0031	1.0002
Japan / AR-MOM vs. AR-MOM-CR	0.9965	0.9904	0.9921	0.9906	0.9911
UK / AR vs. AR-MOM	1.0715	1.0440	1.0347	1.0252	1.0196
UK / AR-MOM vs. AR-MOM-CR1	0.9998	0.9996	0.9995	0.9995	0.9996
UK / AR-MOM vs. AR-MOM-CR2	0.9999	0.9997	0.9986	0.9982	0.9972
UK / AR-MOM vs. AR-MOM-CR3	0.9998	0.9997	0.9981	0.9972	0.9951
UK / AR-MOM vs. AR-MOM-CR4	0.9999	0.9997	0.9990	0.9983	0.9956
UK / AR-MOM vs. AR-MOM-CR	0.9996	0.9990	0.9980	0.9969	0.9938
US / AR vs. AR-MOM	1.3608	1.1537	1.0960	1.0660	1.0471
US / AR-MOM vs. AR-MOM-CR1	0.9998	1.0000	0.9999	1.0001	0.9998
US / AR-MOM vs. AR-MOM-CR2	0.9998	0.9997	0.9996	0.9996	0.9997
US / AR-MOM vs. AR-MOM-CR3	0.9999	0.9998	0.9999	0.9999	0.9995
US / AR-MOM vs. AR-MOM-CR4	0.9995	0.9992	1.0004	1.0017	1.0007
US / AR-MOM vs. AR-MOM-CR	0.9991	0.9985	0.9998	1.0020	1.0004

Table 2: MAFE ratios for a recursive estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	1.6032	1.2679	1.1643	1.0990	1.0607
Canada / AR-MOM vs. AR-MOM-CR1	0.9956	0.9967	0.9967	0.9984	0.9997
Canada / AR-MOM vs. AR-MOM-CR2	1.0078	1.0162	1.0140	0.9826	0.9491
Canada / AR-MOM vs. AR-MOM-CR3	1.0034	1.0131	1.0154	1.0040	1.0000
Canada / AR-MOM vs. AR-MOM-CR4	0.9943	0.9960	0.9976	0.9986	1.0000
Canada / AR-MOM vs. AR-MOM-CR	0.9955	1.0137	1.0050	0.9658	0.9349
France / AR vs. AR-MOM	1.9889	1.2860	1.1200	1.0741	1.0496
France / AR-MOM vs. AR-MOM-CR1	0.9996	0.9993	0.9984	0.9992	0.9992
France / AR-MOM vs. AR-MOM-CR2	0.9978	0.9985	0.9986	0.9977	0.9978
France / AR-MOM vs. AR-MOM-CR3	0.9979	0.9989	0.9983	0.9972	0.9966
France / AR-MOM vs. AR-MOM-CR4	0.9978	0.9987	0.9985	0.9972	0.9972
France / AR-MOM vs. AR-MOM-CR	0.9925	0.9904	0.9889	0.9923	0.9941
Germany / AR vs. AR-MOM	0.7423	0.9193	1.0516	1.1014	1.1220
Germany / AR-MOM vs. AR-MOM-CR1	0.9887	0.9961	0.9976	0.9855	0.9802
Germany / AR-MOM vs. AR-MOM-CR2	0.9952	0.9808	0.9559	0.9472	0.9571
Germany / AR-MOM vs. AR-MOM-CR3	0.9929	0.9750	0.9470	0.9376	0.9480
Germany / AR-MOM vs. AR-MOM-CR4	0.9977	0.9933	0.9896	0.9860	0.9881
Germany / AR-MOM vs. AR-MOM-CR	0.9724	0.9396	0.9130	0.9069	0.9193
Italy / AR vs. AR-MOM	1.0683	1.0058	0.9869	0.9750	0.9613
Italy / AR-MOM vs. AR-MOM-CR1	0.9986	0.9993	0.9990	0.9973	0.9963
Italy / AR-MOM vs. AR-MOM-CR2	1.0010	1.0014	0.9996	0.9992	0.9982
Italy / AR-MOM vs. AR-MOM-CR3	1.0027	1.0016	0.9986	0.9973	0.9960
Italy / AR-MOM vs. AR-MOM-CR4	1.0067	1.0019	0.9975	0.9967	0.9998
Italy / AR-MOM vs. AR-MOM-CR	1.0061	0.9977	0.9933	0.9893	0.9897
Japan / AR vs. AR-MOM	1.2832	1.1449	1.0759	1.0410	1.0241
Japan / AR-MOM vs. AR-MOM-CR1	0.9788	0.9872	0.9890	0.9956	0.9952
Japan / AR-MOM vs. AR-MOM-CR2	1.0000	0.9936	0.9914	0.9936	0.9943
Japan / AR-MOM vs. AR-MOM-CR3	0.9983	0.9952	0.9926	0.9947	0.9960
Japan / AR-MOM vs. AR-MOM-CR4	0.9481	0.9445	0.9494	0.9336	0.9189
Japan / AR-MOM vs. AR-MOM-CR	0.9064	0.9283	0.9347	0.9258	0.9141
UK / AR vs. AR-MOM	0.9124	1.0128	1.0555	1.0488	1.0471
UK / AR-MOM vs. AR-MOM-CR1	0.9980	0.9954	0.9966	0.9979	0.9988
UK / AR-MOM vs. AR-MOM-CR2	0.9992	0.9944	0.9861	0.9850	0.9810
UK / AR-MOM vs. AR-MOM-CR3	0.9992	0.9938	0.9853	0.9821	0.9764
UK / AR-MOM vs. AR-MOM-CR4	0.9967	0.9917	0.9918	0.9898	0.9849
UK / AR-MOM vs. AR-MOM-CR	0.9947	0.9912	1.0030	1.0095	1.0091
US / AR vs. AR-MOM	1.3659	1.1501	1.0856	1.0501	1.0236
US / AR-MOM vs. AR-MOM-CR1	0.9995	1.0002	0.9996	0.9995	0.9993
US / AR-MOM vs. AR-MOM-CR2	1.0004	0.9995	0.9996	0.9991	0.9982
US / AR-MOM vs. AR-MOM-CR3	0.9988	1.0001	1.0005	1.0000	0.9995
US / AR-MOM vs. AR-MOM-CR4	0.9969	0.9968	0.9992	1.0000	0.9995
US / AR-MOM vs. AR-MOM-CR	0.9953	0.9953	0.9939	0.9941	0.9935

Table 3: RMSFE ratios for a rolling estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	1.7552	1.3109	1.1441	1.0802	1.0524
Canada / AR-MOM vs. AR-MOM-CR1	0.9981	0.9983	0.9984	0.9978	0.9974
Canada / AR-MOM vs. AR-MOM-CR2	1.0020	1.0052	1.0079	0.9951	0.9700
Canada / AR-MOM vs. AR-MOM-CR3	0.9996	0.9985	0.9964	0.9915	0.9902
Canada / AR-MOM vs. AR-MOM-CR4	0.9982	0.9964	0.9936	0.9956	0.9970
Canada / AR-MOM vs. AR-MOM-CR	0.9948	0.9910	0.9722	0.9396	0.9023
France / AR vs. AR-MOM	1.6846	1.2559	1.1196	1.0687	1.0521
France / AR-MOM vs. AR-MOM-CR1	0.9995	0.9980	0.9993	0.9988	0.9981
France / AR-MOM vs. AR-MOM-CR2	0.9945	0.9961	0.9943	0.9933	0.9905
France / AR-MOM vs. AR-MOM-CR3	0.9952	0.9967	0.9948	0.9933	0.9907
France / AR-MOM vs. AR-MOM-CR4	0.9951	0.9964	0.9938	0.9922	0.9894
France / AR-MOM vs. AR-MOM-CR	0.9857	0.9877	0.9866	0.9841	0.9790
Germany / AR vs. AR-MOM	1.0185	1.0456	1.0425	1.0478	1.0678
Germany / AR-MOM vs. AR-MOM-CR1	0.9979	0.9986	0.9992	0.9984	0.9975
Germany / AR-MOM vs. AR-MOM-CR2	1.0001	1.0008	1.0036	1.0058	1.0075
Germany / AR-MOM vs. AR-MOM-CR3	1.0002	1.0013	1.0040	1.0063	1.0080
Germany / AR-MOM vs. AR-MOM-CR4	0.9998	0.9996	1.0013	1.0031	1.0047
Germany / AR-MOM vs. AR-MOM-CR	0.9985	0.9991	1.0005	1.0010	1.0021
Italy / AR vs. AR-MOM	1.0714	1.0456	1.0307	1.0262	1.0184
Italy / AR-MOM vs. AR-MOM-CR1	0.9993	0.9986	0.9981	0.9979	0.9978
Italy / AR-MOM vs. AR-MOM-CR2	0.9992	0.9985	0.9966	0.9963	0.9964
Italy / AR-MOM vs. AR-MOM-CR3	0.9989	0.9984	0.9965	0.9962	0.9964
Italy / AR-MOM vs. AR-MOM-CR4	0.9974	0.9895	0.9853	0.9860	0.9796
Italy / AR-MOM vs. AR-MOM-CR	0.9935	0.9808	0.9760	0.9723	0.9644
Japan / AR vs. AR-MOM	1.1301	1.0792	1.1007	1.0713	1.0317
Japan / AR-MOM vs. AR-MOM-CR1	0.9984	0.9943	0.9895	0.9892	0.9923
Japan / AR-MOM vs. AR-MOM-CR2	0.9996	0.9527	0.9481	0.9755	0.9831
Japan / AR-MOM vs. AR-MOM-CR3	0.9951	0.9691	0.9711	0.9829	0.9895
Japan / AR-MOM vs. AR-MOM-CR4	0.9913	0.9949	1.0056	1.0115	1.0130
Japan / AR-MOM vs. AR-MOM-CR	0.9810	0.9693	0.9680	0.9917	0.9997
UK / AR vs. AR-MOM	0.8046	0.7841	0.9526	0.9683	0.9548
UK / AR-MOM vs. AR-MOM-CR1	1.0000	0.9999	0.9997	0.9996	0.9995
UK / AR-MOM vs. AR-MOM-CR2	1.0000	0.9998	0.9991	0.9988	0.9987
UK / AR-MOM vs. AR-MOM-CR3	0.9999	0.9996	0.9988	0.9985	0.9983
UK / AR-MOM vs. AR-MOM-CR4	0.9994	0.9989	0.9979	0.9976	0.9977
UK / AR-MOM vs. AR-MOM-CR	0.9988	0.9986	0.9981	0.9995	1.0008
US / AR vs. AR-MOM	0.8787	0.9951	0.9578	0.9490	0.9655
US / AR-MOM vs. AR-MOM-CR1	0.9997	1.0003	1.0014	1.0018	1.0002
US / AR-MOM vs. AR-MOM-CR2	1.0004	0.9995	0.9994	0.9994	0.9996
US / AR-MOM vs. AR-MOM-CR3	1.0011	0.9974	0.9943	0.9942	0.9967
US / AR-MOM vs. AR-MOM-CR4	1.0009	0.9968	1.0005	1.0028	1.0003
US / AR-MOM vs. AR-MOM-CR	1.0080	0.9912	0.9928	0.9953	0.9936

Table 4: RMSFE ratios for a recursive estimation window (50% of the forecasts deleted)

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	2.0107	1.3590	1.1531	1.0840	1.0568
Canada / AR-MOM vs. AR-MOM-CR1	0.9998	0.9981	0.9995	0.9994	0.9999
Canada / AR-MOM vs. AR-MOM-CR2	0.9987	0.9990	0.9991	0.9975	0.9950
Canada / AR-MOM vs. AR-MOM-CR3	0.9990	0.9983	0.9974	0.9972	0.9976
Canada / AR-MOM vs. AR-MOM-CR4	0.9981	0.9980	0.9989	1.0003	1.0005
Canada / AR-MOM vs. AR-MOM-CR	0.9955	0.9931	0.9962	0.9927	0.9867
France / AR vs. AR-MOM	1.8771	1.3148	1.1553	1.0907	1.0627
France / AR-MOM vs. AR-MOM-CR1	1.0007	0.9998	0.9993	0.9996	1.0001
France / AR-MOM vs. AR-MOM-CR2	0.9983	0.9994	1.0005	1.0006	1.0001
France / AR-MOM vs. AR-MOM-CR3	0.9982	0.9991	0.9998	0.9995	0.9989
France / AR-MOM vs. AR-MOM-CR4	0.9985	0.9994	1.0003	1.0002	0.9996
France / AR-MOM vs. AR-MOM-CR	1.0026	1.0022	0.9996	0.9988	0.9975
Germany / AR vs. AR-MOM	0.4319	0.5108	0.5562	0.5611	0.5536
Germany / AR-MOM vs. AR-MOM-CR1	1.0000	1.0004	1.0015	0.9953	0.9866
Germany / AR-MOM vs. AR-MOM-CR2	0.9998	0.9988	0.9835	0.9697	0.9677
Germany / AR-MOM vs. AR-MOM-CR3	0.9992	0.9968	0.9788	0.9647	0.9626
Germany / AR-MOM vs. AR-MOM-CR4	0.9999	1.0001	1.0007	0.9996	0.9994
Germany / AR-MOM vs. AR-MOM-CR	0.9927	0.9751	0.9449	0.9235	0.9177
Italy / AR vs. AR-MOM	1.1044	0.9937	0.9628	0.9288	0.9130
Italy / AR-MOM vs. AR-MOM-CR1	1.0008	0.9996	0.9970	0.9951	0.9920
Italy / AR-MOM vs. AR-MOM-CR2	1.0001	0.9998	1.0000	0.9997	0.9990
Italy / AR-MOM vs. AR-MOM-CR3	1.0001	0.9997	0.9992	0.9988	0.9976
Italy / AR-MOM vs. AR-MOM-CR4	1.0023	1.0035	1.0042	1.0058	1.0099
Italy / AR-MOM vs. AR-MOM-CR	1.0029	1.0024	1.0004	1.0000	1.0000
Japan / AR vs. AR-MOM	1.4454	1.1434	1.0244	0.9574	0.9545
Japan / AR-MOM vs. AR-MOM-CR1	0.9900	0.9963	0.9993	0.9989	0.9989
Japan / AR-MOM vs. AR-MOM-CR2	0.9999	0.9982	0.9972	0.9976	0.9978
Japan / AR-MOM vs. AR-MOM-CR3	0.9996	0.9935	0.9907	0.9932	0.9945
Japan / AR-MOM vs. AR-MOM-CR4	0.9937	0.9827	0.9708	0.9694	0.9661
Japan / AR-MOM vs. AR-MOM-CR	0.9566	0.9597	0.9621	0.9629	0.9626
UK / AR vs. AR-MOM	1.2122	1.1322	1.0837	1.0613	1.0549
UK / AR-MOM vs. AR-MOM-CR1	0.9999	0.9993	0.9998	0.9999	1.0000
UK / AR-MOM vs. AR-MOM-CR2	0.9997	0.9992	0.9969	0.9958	0.9960
UK / AR-MOM vs. AR-MOM-CR3	0.9994	0.9987	0.9955	0.9936	0.9930
UK / AR-MOM vs. AR-MOM-CR4	0.9997	0.9999	0.9994	1.0002	1.0017
UK / AR-MOM vs. AR-MOM-CR	0.9995	0.9979	0.9945	0.9918	0.9888
US / AR vs. AR-MOM	1.6017	1.1632	1.0516	1.0135	0.9940
US / AR-MOM vs. AR-MOM-CR1	0.9999	1.0001	1.0001	0.9999	0.9999
US / AR-MOM vs. AR-MOM-CR2	1.0001	0.9999	1.0000	0.9996	0.9989
US / AR-MOM vs. AR-MOM-CR3	0.9997	0.9997	0.9997	1.0000	0.9995
US / AR-MOM vs. AR-MOM-CR4	0.9996	0.9996	1.0003	1.0016	1.0005
US / AR-MOM vs. AR-MOM-CR	0.9994	0.9989	0.9982	0.9976	0.9944

Table 5: RMSFE ratios for a rolling estimation window (50% of the forecasts deleted)

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	1.9261	1.3577	1.1533	1.0803	1.0522
Canada / AR-MOM vs. AR-MOM-CR1	0.9988	0.9991	0.9990	0.9974	0.9974
Canada / AR-MOM vs. AR-MOM-CR2	0.9996	0.9960	0.9913	0.9776	0.9575
Canada / AR-MOM vs. AR-MOM-CR3	0.9991	0.9957	0.9880	0.9792	0.9753
Canada / AR-MOM vs. AR-MOM-CR4	1.0010	0.9970	0.9966	0.9982	0.9983
Canada / AR-MOM vs. AR-MOM-CR	0.9974	0.9809	0.9459	0.9101	0.8696
France / AR vs. AR-MOM	1.8184	1.3076	1.1462	1.0796	1.0528
France / AR-MOM vs. AR-MOM-CR1	0.9991	0.9981	0.9996	0.9994	0.9989
France / AR-MOM vs. AR-MOM-CR2	0.9903	0.9940	0.9945	0.9906	0.9852
France / AR-MOM vs. AR-MOM-CR3	0.9918	0.9952	0.9953	0.9909	0.9855
France / AR-MOM vs. AR-MOM-CR4	0.9919	0.9948	0.9939	0.9891	0.9834
France / AR-MOM vs. AR-MOM-CR	0.9804	0.9848	0.9887	0.9809	0.9726
Germany / AR vs. AR-MOM	0.4917	0.5957	0.7039	0.7725	0.7530
Germany / AR-MOM vs. AR-MOM-CR1	1.0005	0.9971	1.0020	0.9743	0.9442
Germany / AR-MOM vs. AR-MOM-CR2	1.0002	1.0007	0.9921	0.9686	0.9699
Germany / AR-MOM vs. AR-MOM-CR3	1.0001	1.0004	0.9850	0.9620	0.9651
Germany / AR-MOM vs. AR-MOM-CR4	1.0001	0.9991	1.0022	1.0027	1.0010
Germany / AR-MOM vs. AR-MOM-CR	0.9992	0.9826	0.9169	0.8416	0.8222
Italy / AR vs. AR-MOM	1.1500	1.0662	1.0228	0.9984	0.9969
Italy / AR-MOM vs. AR-MOM-CR1	0.9992	0.9981	0.9967	0.9947	0.9953
Italy / AR-MOM vs. AR-MOM-CR2	0.9981	0.9943	0.9884	0.9888	0.9905
Italy / AR-MOM vs. AR-MOM-CR3	0.9981	0.9942	0.9898	0.9907	0.9930
Italy / AR-MOM vs. AR-MOM-CR4	0.9973	0.9910	0.9889	0.9901	0.9889
Italy / AR-MOM vs. AR-MOM-CR	0.9916	0.9756	0.9593	0.9452	0.9372
Japan / AR vs. AR-MOM	1.5081	1.1852	1.0887	1.0382	1.0160
Japan / AR-MOM vs. AR-MOM-CR1	1.0005	0.9972	0.9924	0.9916	0.9903
Japan / AR-MOM vs. AR-MOM-CR2	1.0004	0.9983	0.9982	0.9982	0.9990
Japan / AR-MOM vs. AR-MOM-CR3	0.9996	0.9952	0.9958	0.9959	0.9974
Japan / AR-MOM vs. AR-MOM-CR4	0.9982	0.9960	0.9920	0.9882	0.9894
Japan / AR-MOM vs. AR-MOM-CR	0.9944	0.9841	0.9794	0.9757	0.9769
UK / AR vs. AR-MOM	1.1972	1.1129	1.0690	1.0343	1.0049
UK / AR-MOM vs. AR-MOM-CR1	0.9998	0.9995	0.9996	0.9995	0.9995
UK / AR-MOM vs. AR-MOM-CR2	1.0001	0.9997	0.9988	0.9986	0.9991
UK / AR-MOM vs. AR-MOM-CR3	1.0001	0.9996	0.9987	0.9986	0.9994
UK / AR-MOM vs. AR-MOM-CR4	0.9998	0.9993	0.9983	0.9988	1.0002
UK / AR-MOM vs. AR-MOM-CR	1.0005	0.9988	0.9973	0.9980	1.0005
US / AR vs. AR-MOM	1.5284	1.1294	1.0108	0.9593	0.9199
US / AR-MOM vs. AR-MOM-CR1	0.9987	0.9990	0.9996	0.9992	0.9995
US / AR-MOM vs. AR-MOM-CR2	0.9999	0.9996	0.9997	0.9993	0.9989
US / AR-MOM vs. AR-MOM-CR3	0.9990	0.9993	0.9988	0.9994	0.9993
US / AR-MOM vs. AR-MOM-CR4	0.9994	0.9997	1.0002	1.0002	0.9995
US / AR-MOM vs. AR-MOM-CR	0.9960	0.9974	0.9968	0.9934	0.9923

Table 6: RMSFE ratios for a recursive estimation window (discounting of forecast errors)

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	2.2690	1.3688	1.1537	1.1049	1.0828
Canada / AR-MOM vs. AR-MOM-CR1	1.0034	0.9947	0.9968	0.9996	1.0004
Canada / AR-MOM vs. AR-MOM-CR2	1.0035	1.0034	1.0060	0.9967	0.9859
Canada / AR-MOM vs. AR-MOM-CR3	0.9989	1.0002	1.0004	0.9943	0.9881
Canada / AR-MOM vs. AR-MOM-CR4	0.9996	0.9980	1.0008	1.0022	1.0021
Canada / AR-MOM vs. AR-MOM-CR	1.0038	0.9974	0.9971	0.9902	0.9838
France / AR vs. AR-MOM	2.0836	1.3548	1.1652	1.1173	1.0811
France / AR-MOM vs. AR-MOM-CR1	1.0005	1.0012	0.9998	0.9998	1.0012
France / AR-MOM vs. AR-MOM-CR2	0.9989	0.9983	0.9954	0.9915	0.9959
France / AR-MOM vs. AR-MOM-CR3	0.9989	0.9984	0.9954	0.9911	0.9957
France / AR-MOM vs. AR-MOM-CR4	0.9987	0.9981	0.9942	0.9884	0.9933
France / AR-MOM vs. AR-MOM-CR	1.0018	1.0018	1.0023	0.9971	0.9948
Germany / AR vs. AR-MOM	0.4813	0.6310	0.7057	0.6864	0.6394
Germany / AR-MOM vs. AR-MOM-CR1	1.0000	1.0012	1.0039	0.9961	0.9830
Germany / AR-MOM vs. AR-MOM-CR2	0.9950	0.9957	0.9877	0.9899	0.9958
Germany / AR-MOM vs. AR-MOM-CR3	0.9929	0.9901	0.9771	0.9793	0.9863
Germany / AR-MOM vs. AR-MOM-CR4	0.9997	1.0005	1.0042	1.0092	1.0117
Germany / AR-MOM vs. AR-MOM-CR	0.9829	0.9552	0.9381	0.9360	0.9354
Italy / AR vs. AR-MOM	1.3138	1.0784	1.0150	0.9897	0.9798
Italy / AR-MOM vs. AR-MOM-CR1	1.0011	0.9982	1.0007	0.9977	0.9974
Italy / AR-MOM vs. AR-MOM-CR2	1.0019	1.0034	1.0011	1.0006	1.0011
Italy / AR-MOM vs. AR-MOM-CR3	1.0039	1.0044	1.0005	1.0001	1.0001
Italy / AR-MOM vs. AR-MOM-CR4	1.0076	1.0051	1.0014	1.0057	1.0198
Italy / AR-MOM vs. AR-MOM-CR	1.0101	1.0018	0.9973	1.0010	1.0144
Japan / AR vs. AR-MOM	1.7611	1.4559	1.3563	1.3207	1.2615
Japan / AR-MOM vs. AR-MOM-CR1	1.0051	1.0002	0.9993	0.9998	0.9996
Japan / AR-MOM vs. AR-MOM-CR2	0.9998	1.0084	1.0118	1.0105	1.0079
Japan / AR-MOM vs. AR-MOM-CR3	1.0035	1.0084	1.0096	1.0148	1.0108
Japan / AR-MOM vs. AR-MOM-CR4	0.9334	1.0143	1.0800	1.1646	1.2255
Japan / AR-MOM vs. AR-MOM-CR	0.9400	1.0140	1.0888	1.1616	1.2261
UK / AR vs. AR-MOM	1.7098	1.2985	1.0898	0.9916	0.9226
UK / AR-MOM vs. AR-MOM-CR1	0.9979	0.9991	0.9997	0.9994	0.9997
UK / AR-MOM vs. AR-MOM-CR2	1.0000	0.9992	0.9989	1.0006	0.9987
UK / AR-MOM vs. AR-MOM-CR3	0.9999	0.9989	0.9985	1.0012	0.9975
UK / AR-MOM vs. AR-MOM-CR4	0.9995	0.9983	0.9975	0.9976	0.9948
UK / AR-MOM vs. AR-MOM-CR	0.9977	0.9981	0.9987	1.0024	0.9969
US / AR vs. AR-MOM	1.8939	1.1540	1.0597	1.0153	0.9928
US / AR-MOM vs. AR-MOM-CR1	1.0001	0.9997	0.9994	0.9989	0.9992
US / AR-MOM vs. AR-MOM-CR2	0.9997	0.9998	0.9997	0.9996	1.0002
US / AR-MOM vs. AR-MOM-CR3	1.0000	0.9994	0.9987	0.9981	0.9994
US / AR-MOM vs. AR-MOM-CR4	0.9999	0.9994	0.9984	0.9944	0.9950
US / AR-MOM vs. AR-MOM-CR	0.9999	0.9985	0.9963	0.9923	0.9934

Table 7: RMSFE ratios for a rolling estimation window (discounting of forecast errors)

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR vs. AR-MOM	2.0897	1.3735	1.1591	1.0970	1.0721
Canada / AR-MOM vs. AR-MOM-CR1	0.9985	0.9982	0.9988	0.9979	1.0008
Canada / AR-MOM vs. AR-MOM-CR2	0.9813	0.9804	0.9798	0.9748	0.9645
Canada / AR-MOM vs. AR-MOM-CR3	0.9794	0.9601	0.9303	0.9083	0.8816
Canada / AR-MOM vs. AR-MOM-CR4	1.0036	0.9995	0.9988	1.0012	1.0015
Canada / AR-MOM vs. AR-MOM-CR	0.9808	0.9526	0.9072	0.8712	0.8458
France / AR vs. AR-MOM	2.0142	1.3740	1.1708	1.1079	1.0673
France / AR-MOM vs. AR-MOM-CR1	0.9998	1.0005	1.0021	0.9992	0.9998
France / AR-MOM vs. AR-MOM-CR2	0.9938	0.9971	0.9908	0.9822	0.9750
France / AR-MOM vs. AR-MOM-CR3	0.9951	0.9976	0.9920	0.9833	0.9757
France / AR-MOM vs. AR-MOM-CR4	0.9939	0.9967	0.9900	0.9793	0.9693
France / AR-MOM vs. AR-MOM-CR	0.9792	0.9882	0.9961	0.9733	0.9543
Germany / AR vs. AR-MOM	1.4643	1.3153	1.1935	1.1244	1.0843
Germany / AR-MOM vs. AR-MOM-CR1	0.9989	1.0005	1.0047	1.0033	1.0008
Germany / AR-MOM vs. AR-MOM-CR2	0.9992	0.9920	0.9920	0.9929	0.9892
Germany / AR-MOM vs. AR-MOM-CR3	0.9981	0.9927	0.9929	0.9937	0.9887
Germany / AR-MOM vs. AR-MOM-CR4	0.9978	0.9881	0.9898	0.9923	0.9912
Germany / AR-MOM vs. AR-MOM-CR	0.9873	0.9960	0.9955	0.9916	0.9847
Italy / AR vs. AR-MOM	1.4029	1.1808	1.0945	1.0683	1.0497
Italy / AR-MOM vs. AR-MOM-CR1	0.9987	1.0037	1.0032	0.9984	0.9984
Italy / AR-MOM vs. AR-MOM-CR2	0.9983	0.9984	0.9996	1.0005	1.0029
Italy / AR-MOM vs. AR-MOM-CR3	0.9978	0.9980	0.9997	1.0010	1.0046
Italy / AR-MOM vs. AR-MOM-CR4	0.9975	0.9990	0.9969	0.9951	1.0053
Italy / AR-MOM vs. AR-MOM-CR	0.9982	0.9992	0.9961	0.9928	0.9954
Japan / AR vs. AR-MOM	1.6847	1.2700	1.0471	0.9242	0.8936
Japan / AR-MOM vs. AR-MOM-CR1	0.9750	0.9897	0.9991	1.0035	1.0014
Japan / AR-MOM vs. AR-MOM-CR2	1.0038	1.0003	0.9998	0.9997	0.9995
Japan / AR-MOM vs. AR-MOM-CR3	1.0035	1.0000	0.9995	0.9997	0.9996
Japan / AR-MOM vs. AR-MOM-CR4	0.9929	1.0708	1.0836	1.0984	1.0925
Japan / AR-MOM vs. AR-MOM-CR	0.9665	1.0481	1.0794	1.0988	1.0902
UK / AR vs. AR-MOM	1.6020	1.3016	1.1255	1.0580	1.0083
UK / AR-MOM vs. AR-MOM-CR1	0.9975	1.0011	0.9999	0.9995	0.9999
UK / AR-MOM vs. AR-MOM-CR2	1.0009	1.0003	0.9991	0.9996	0.9998
UK / AR-MOM vs. AR-MOM-CR3	0.9992	0.9997	0.9985	0.9989	0.9995
UK / AR-MOM vs. AR-MOM-CR4	0.9997	0.9951	0.9953	0.9946	0.9895
UK / AR-MOM vs. AR-MOM-CR	0.9778	0.9792	0.9801	0.9725	0.9726
US / AR vs. AR-MOM	1.7511	1.1482	1.0863	1.0622	1.0413
US / AR-MOM vs. AR-MOM-CR1	1.0000	1.0000	0.9991	0.9980	0.9983
US / AR-MOM vs. AR-MOM-CR2	0.9997	0.9986	0.9971	0.9943	0.9962
US / AR-MOM vs. AR-MOM-CR3	1.0000	0.9989	0.9972	0.9942	0.9979
US / AR-MOM vs. AR-MOM-CR4	0.9991	0.9991	0.9994	0.9986	0.9996
US / AR-MOM vs. AR-MOM-CR	0.9986	0.9988	0.9986	0.9952	0.9976

Table 8: Results for the optimal stepwise predictor selection approach (RMSFE ratios)

Panel A: Recursive estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR-MOM vs. AR-MOM-R2	0.9937	0.9891	0.9950	0.9796	0.9609
Canada / AR-MOM vs. AR-MOM-BIC	0.9973	0.9926	0.9942	0.9889	0.9648
Canada / AR-MOM vs. AR-MOM-CP	0.9953	0.9905	0.9939	0.9810	0.9588
France / AR-MOM vs. AR-MOM-R2	0.9983	0.9989	0.9975	0.9988	0.9962
France / AR-MOM vs. AR-MOM-BIC	0.9990	0.9971	0.9985	0.9979	0.9949
France / AR-MOM vs. AR-MOM-CP	0.9985	0.9973	0.9986	0.9990	0.9963
Germany / AR-MOM vs. AR-MOM-R2	0.9988	0.9998	1.0012	1.0023	1.0030
Germany / AR-MOM vs. AR-MOM-BIC	0.9985	0.9992	1.0000	1.0019	1.0031
Germany / AR-MOM vs. AR-MOM-CP	0.9982	0.9994	1.0011	1.0018	1.0030
Italy / AR-MOM vs. AR-MOM-R2	0.9997	0.9958	0.9901	0.9913	0.9863
Italy / AR-MOM vs. AR-MOM-BIC	0.9997	0.9959	0.9943	0.9956	0.9909
Italy / AR-MOM vs. AR-MOM-CP	0.9997	0.9959	0.9927	0.9931	0.9861
Japan / AR-MOM vs. AR-MOM-R2	0.9959	0.9915	0.9925	0.9918	0.9926
Japan / AR-MOM vs. AR-MOM-BIC	0.9989	0.9948	0.9965	0.9980	0.9956
Japan / AR-MOM vs. AR-MOM-CP	0.9930	0.9914	0.9922	0.9916	0.9925
UK / AR-MOM vs. AR-MOM-R2	0.9993	0.9982	0.9987	0.9978	0.9952
UK / AR-MOM vs. AR-MOM-BIC	0.9995	0.9992	0.9978	0.9965	0.9954
UK / AR-MOM vs. AR-MOM-CP	0.9995	0.9991	0.9987	0.9978	0.9954
US / AR-MOM vs. AR-MOM-R2	0.9993	0.9984	0.9991	1.0019	1.0003
US / AR-MOM vs. AR-MOM-BIC	0.9992	0.9988	1.0000	1.0017	0.9994
US / AR-MOM vs. AR-MOM-CP	0.9993	0.9987	0.9987	1.0021	1.0002

Panel B: Rolling estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR-MOM vs. AR-MOM-R2	0.9963	0.9953	0.9750	0.9491	0.9047
Canada / AR-MOM vs. AR-MOM-BIC	0.9983	0.9974	0.9808	0.9653	0.9164
Canada / AR-MOM vs. AR-MOM-CP	0.9971	0.9994	0.9779	0.9546	0.9134
France / AR-MOM vs. AR-MOM-R2	0.9875	0.9876	0.9847	0.9835	0.9787
France / AR-MOM vs. AR-MOM-BIC	0.9921	0.9925	0.9867	0.9842	0.9800
France / AR-MOM vs. AR-MOM-CP	0.9901	0.9889	0.9868	0.9844	0.9788
Germany / AR-MOM vs. AR-MOM-R2	0.9984	0.9994	1.0002	1.0003	1.0012
Germany / AR-MOM vs. AR-MOM-BIC	0.9974	0.9984	0.9986	0.9993	1.0013
Germany / AR-MOM vs. AR-MOM-CP	0.9988	0.9996	1.0002	0.9989	1.0012
Italy / AR-MOM vs. AR-MOM-R2	0.9968	0.9844	0.9793	0.9752	0.9649
Italy / AR-MOM vs. AR-MOM-BIC	0.9969	0.9860	0.9848	0.9847	0.9752
Italy / AR-MOM vs. AR-MOM-CP	0.9969	0.9858	0.9818	0.9745	0.9668
Japan / AR-MOM vs. AR-MOM-R2	0.9796	0.9669	0.9689	0.9922	1.0010
Japan / AR-MOM vs. AR-MOM-BIC	0.9773	0.9700	0.9644	1.0029	1.0073
Japan / AR-MOM vs. AR-MOM-CP	0.9798	0.9671	0.9623	0.9923	1.0033
UK / AR-MOM vs. AR-MOM-R2	0.9995	0.9985	0.9987	0.9998	1.0012
UK / AR-MOM vs. AR-MOM-BIC	0.9995	0.9987	0.9990	0.9989	1.0004
UK / AR-MOM vs. AR-MOM-CP	0.9995	0.9986	0.9987	0.9996	1.0012
US / AR-MOM vs. AR-MOM-R2	1.0088	0.9912	0.9946	0.9950	0.9928
US / AR-MOM vs. AR-MOM-BIC	0.9999	0.9969	0.9939	0.9954	0.9955
US / AR-MOM vs. AR-MOM-CP	1.0089	0.9917	0.9936	0.9930	0.9931

Table 9: Results for the optimal stepwise predictor selection approach (MAFE ratios)

Panel A: Recursive estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR-MOM vs. AR-MOM-R2	0.9953	1.0058	1.0057	0.9718	0.9366
Canada / AR-MOM vs. AR-MOM-BIC	0.9999	0.9983	1.0041	0.9834	0.9458
Canada / AR-MOM vs. AR-MOM-CP	0.9971	1.0011	1.0036	0.9727	0.9357
France / AR-MOM vs. AR-MOM-R2	0.9948	0.9920	0.9911	0.9945	0.9942
France / AR-MOM vs. AR-MOM-BIC	0.9982	0.9950	0.9934	0.9938	0.9920
France / AR-MOM vs. AR-MOM-CP	0.9970	0.9911	0.9933	0.9951	0.9941
Germany / AR-MOM vs. AR-MOM-R2	0.9743	0.9450	0.9140	0.9044	0.9179
Germany / AR-MOM vs. AR-MOM-BIC	0.9868	0.9610	0.9153	0.9066	0.9196
Germany / AR-MOM vs. AR-MOM-CP	0.9811	0.9481	0.9149	0.9057	0.9177
Italy / AR-MOM vs. AR-MOM-R2	1.0064	0.9998	0.9935	0.9901	0.9894
Italy / AR-MOM vs. AR-MOM-BIC	1.0064	1.0003	0.9978	0.9960	0.9953
Italy / AR-MOM vs. AR-MOM-CP	1.0064	1.0003	0.9970	0.9937	0.9905
Japan / AR-MOM vs. AR-MOM-R2	0.9061	0.9282	0.9359	0.9292	0.9156
Japan / AR-MOM vs. AR-MOM-BIC	0.9463	0.9374	0.9393	0.9289	0.9169
Japan / AR-MOM vs. AR-MOM-CP	0.9050	0.9303	0.9363	0.9291	0.9163
UK / AR-MOM vs. AR-MOM-R2	0.9950	0.9902	1.0066	1.0116	1.0127
UK / AR-MOM vs. AR-MOM-BIC	0.9966	0.9909	0.9835	1.0028	1.0123
UK / AR-MOM vs. AR-MOM-CP	0.9966	0.9924	1.0066	1.0116	1.0123
US / AR-MOM vs. AR-MOM-R2	0.9956	0.9959	0.9933	0.9932	0.9937
US / AR-MOM vs. AR-MOM-BIC	0.9971	0.9967	0.9989	0.9999	0.9961
US / AR-MOM vs. AR-MOM-CP	0.9970	0.9966	0.9934	0.9942	0.9936

Panel B: Rolling estimation window

Country / Models	h=1	h=3	h=6	h=9	h=12
Canada / AR-MOM vs. AR-MOM-R2	0.9855	1.0050	0.9771	0.9511	0.9154
Canada / AR-MOM vs. AR-MOM-BIC	0.9934	1.0014	0.9835	0.9713	0.9246
Canada / AR-MOM vs. AR-MOM-CP	0.9884	1.0128	0.9789	0.9620	0.9190
France / AR-MOM vs. AR-MOM-R2	0.9752	0.9865	0.9845	0.9850	0.9820
France / AR-MOM vs. AR-MOM-BIC	0.9847	0.9902	0.9883	0.9851	0.9851
France / AR-MOM vs. AR-MOM-CP	0.9761	0.9882	0.9874	0.9860	0.9813
Germany / AR-MOM vs. AR-MOM-R2	0.9584	0.9171	0.8943	0.9017	0.9141
Germany / AR-MOM vs. AR-MOM-BIC	0.9780	0.9398	0.8992	0.9030	0.9196
Germany / AR-MOM vs. AR-MOM-CP	0.9691	0.9294	0.8961	0.9047	0.9157
Italy / AR-MOM vs. AR-MOM-R2	0.9896	0.9729	0.9719	0.9654	0.9611
Italy / AR-MOM vs. AR-MOM-BIC	0.9908	0.9780	0.9777	0.9762	0.9707
Italy / AR-MOM vs. AR-MOM-CP	0.9906	0.9765	0.9746	0.9650	0.9605
Japan / AR-MOM vs. AR-MOM-R2	0.9124	0.9440	0.9548	0.9373	0.9209
Japan / AR-MOM vs. AR-MOM-BIC	0.9244	0.9486	0.9613	0.9458	0.9226
Japan / AR-MOM vs. AR-MOM-CP	0.9130	0.9432	0.9567	0.9378	0.9235
UK / AR-MOM vs. AR-MOM-R2	0.9904	0.9869	0.9839	0.9822	0.9872
UK / AR-MOM vs. AR-MOM-BIC	0.9937	0.9910	0.9842	0.9786	0.9823
UK / AR-MOM vs. AR-MOM-CP	0.9936	0.9880	0.9843	0.9818	0.9860
US / AR-MOM vs. AR-MOM-R2	0.9905	0.9919	0.9904	0.9923	0.9897
US / AR-MOM vs. AR-MOM-BIC	0.9918	0.9948	0.9969	0.9994	0.9897
US / AR-MOM vs. AR-MOM-CP	0.9923	0.9939	0.9948	0.9920	0.9882

Table 10: Quantile causality between climate risks and stock market moments

Canada					
	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	1.4978	1.7393*	91.9725***	32.0321***	7.8300***
CR2–>LEV	4.3687***	6.4757***	27.2468***	8.0222***	1.9234*
CR3–>LEV	1.5033***	1.8139*	85.4449***	29.8660***	7.2901***
CR4–>LEV	5.5286***	8.3368***	19.9097***	5.8775***	1.3974
CR1–>SKEW	2.0905***	3.5621***	4.1122***	2.8427***	2.0953**
CR2–>SKEW	1.1506	2.0198***	3.3858***	2.5277***	1.7042*
CR3–>SKEW	1.8494*	3.4642***	3.9374***	2.6851***	2.0167**
CR4–>SKEW	1.7398*	3.4852***	3.7353***	2.6334***	1.4553
CR1–>KURT	6.1995***	8.7549***	10.2622***	8.8002***	6.1283***
CR2–>KURT	5.1118***	8.0175***	8.8443***	7.1014***	4.7106***
CR3–>KURT	6.4727***	9.0833***	11.0922***	9.3952***	6.1743***
CR4–>KURT	6.0728***	8.9802***	10.2290***	9.0012***	6.1037***

France					
	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	7.8922***	5.6531***	23.0042***	6.7184***	1.5987
CR2–>LEV	7.4188***	4.7035***	28.2205***	8.2587***	1.9777**
CR3–>LEV	7.1398***	4.7934***	27.8810***	8.1611***	1.9553**
CR4–>LEV	6.5322***	4.3240***	30.8706***	9.0443***	2.1694***
CR1–>SKEW	10.4843***	7.2272***	12.0224***	10.8113***	7.3684***
CR2–>SKEW	9.7263***	6.2407***	10.9346***	10.0485***	6.8481***
CR3–>SKEW	9.4921***	6.4972***	11.2255***	9.7436***	6.8134***
CR4–>SKEW	8.9816***	6.0901***	10.6693***	9.4493***	6.6170***
CR1–>KURT	10.9793***	7.4253***	12.1250***	10.3631***	7.2542***
CR2–>KURT	9.8271***	6.6601***	10.8572***	9.6058***	6.2061***
CR3–>KURT	9.3618***	6.7098***	11.2931***	9.5606***	6.4775***
CR4–>KURT	9.0247***	6.4544***	10.8118***	9.0243***	6.0832***

Germany					
	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	1.8264*	2.2431**	89.7564***	33.1427***	8.0836***
CR2–>LEV	1.3063	2.0243**	117.2215***	43.2907***	10.5412***
CR3–>LEV	1.4627	2.2115**	95.5475***	35.7116***	8.7063***
CR4–>LEV	1.1957	2.0275**	111.3745***	41.6249***	10.1343***
CR1–>SKEW	4.2068***	7.8725***	7.9979***	5.6804***	3.3724***
CR2–>SKEW	3.0630***	8.5449***	9.0162***	5.0730***	2.1566***
CR3–>SKEW	3.9450***	7.7203***	7.9870***	5.4234***	3.3621***
CR4–>SKEW	2.7127***	8.3724***	9.0297***	5.2916***	2.3872***
CR1–>KURT	3.7283***	6.2506***	8.2476***	8.8427***	4.4456***
CR2–>KURT	3.0876***	5.2306***	7.4489***	8.1627***	3.5532***
CR3–>KURT	3.6739***	5.6812***	8.3721***	8.5761***	3.9456***
CR4–>KURT	3.5190***	5.2571***	7.8559***	8.3658***	3.7300***

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Italy

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	1.5942	2.9577***	75.4886***	25.8020***	6.2824***
CR2–>LEV	1.0679	1.2462	97.9389***	33.1754***	8.0650***
CR3–>LEV	2.3431	3.8731***	48.6253***	14.2652***	3.4175***
CR4–>LEV	2.0296**	3.4415***	54.8544***	16.0940***	3.8575***
CR1–>SKEW	8.0665***	13.9902***	5.8921***	2.3340***	1.1643
CR2–>SKEW	9.6775***	15.2936***	5.0938***	1.9069*****	1.0428
CR3–>SKEW	9.6126***	15.2693***	5.8803***	2.2146***	1.1819
CR4–>SKEW	10.1131***	16.3069***	6.1359***	2.2592***	1.1598
CR1–>KURT	8.8021***	14.7119***	6.6057***	3.2732***	1.8952
CR2–>KURT	10.8965***	19.9517***	6.7015***	2.6355***	1.3865
CR3–>KURT	10.8965***	19.9517***	6.7015***	2.6355***	1.3865
CR4–>KURT	11.9122***	21.5946***	6.9944***	2.6055***	1.3554

Japan

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	1.0090	1.7932*	86.9123***	33.4591***	8.1734***
CR2–>LEV	1.8338	1.1615*	112.5297***	56.7905***	13.8649***
CR3–>LEV	3.9203	4.8826***	34.1961***	10.0578***	2.4181**
CR4–>LEV	1.0386	1.3249***	112.2820***	32.9812***	7.8648***
CR1–>SKEW	6.0102***	7.1255***	3.4002***	2.9397***	1.8928*
CR2–>SKEW	8.1390***	7.8728***	4.2918***	3.0540***	2.0114**
CR3–>SKEW	8.5571***	9.1759***	2.2244***	1.0460	0.6812
CR4–>SKEW	13.7893***	21.7054***	9.3734***	3.6441***	1.2782
CR1–>KURT	7.8088***	10.9723***	10.0109***	7.5958***	5.1426***
CR2–>KURT	9.3512***	19.0372***	10.2802***	4.5657***	2.4813***
CR3–>KURT	8.4489***	13.1936***	8.0366***	4.4609***	2.3887***
CR4–>KURT	13.7893***	21.7054***	9.3734***	3.6441***	1.2782

UK

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	1.6138	2.4345***	194.3323***	71.7660***	17.5420***
CR2–>LEV	5.1310***	6.6179***	10.2200***	13.6397***	10.7775***
CR3–>LEV	1.7439*	1.8655*	210.0351***	78.6779***	19.2301***
CR4–>LEV	1.7343*	1.6790*	227.5496***	85.4019***	20.8710***
CR1–>SKEW	5.3069***	7.4690***	9.3459***	13.8428***	10.9803***
CR2–>SKEW	5.3069***	7.4690***	9.3459***	13.8428***	10.9803***
CR3–>SKEW	5.1310***	6.6179***	10.2200***	13.6397***	10.7775***
CR4–>SKEW	4.8513***	6.1309***	9.8515***	13.7905***	11.2422***
CR1–>KURT	9.4234***	12.6813***	11.7096***	8.6022***	6.7766***
CR2–>KURT	9.7315***	12.6514***	9.9259***	8.3293***	5.9110***
CR3–>KURT	9.4412***	12.2899***	11.0056***	7.3879***	5.7274***
CR4–>KURT	9.6464***	12.2148***	10.3582***	6.7688***	5.3893***

US

	Quantiles				
	0.1	0.25	0.5	0.75	0.9
CR1–>LEV	8.2779***	11.7762***	29.6758***	8.7010***	2.0696**
CR2–>LEV	6.7967***	9.6414***	39.5453***	11.5800***	2.7752***
CR3–>LEV	7.6296***	11.6130***	31.9295***	9.3309***	2.2254**
CR4–>LEV	6.0168***	8.8138***	43.1347***	12.6594***	3.0374***
CR1–>SKEW	5.4382***	8.6904***	9.9798***	8.3495***	6.5274***
CR2–>SKEW	4.0497***	6.4134***	7.8359***	6.8463***	6.3471***
CR3–>SKEW	4.9730***	7.8084***	8.4092***	7.8795***	6.5663***
CR4–>SKEW	4.0501***	6.4653***	6.6500***	5.8199***	6.0277***
CR1–>KURT	6.6547***	8.0887***	9.5206***	8.2255***	5.2138***
CR2–>KURT	6.5073***	6.8945***	7.4919***	6.1029***	3.9002***
CR3–>KURT	6.6717***	7.8321***	8.0959***	7.7029***	4.6618***
CR4–>KURT	6.4571***	5.9593***	6.3552***	6.2074***	3.8690***

Note: Entries report the standard normal test statistic for the hypothesis that there is no Granger causality for a particular quantile running from a specific climate risks predictor (CR_i, i = 1, 2, 3, 4) to a particular moment (LEV, $SKEW$, $KURT$) of stock returns; ***, ** and * indicates rejection of the null hypothesis at 1% (Critical value: 2.5750), 5% (Critical value: 1.96), and 10% (Critical value: 1.645) level of significance, respectively.

Figure 1: Quantile regression results for a recursive estimation window (RMSFE ratios)

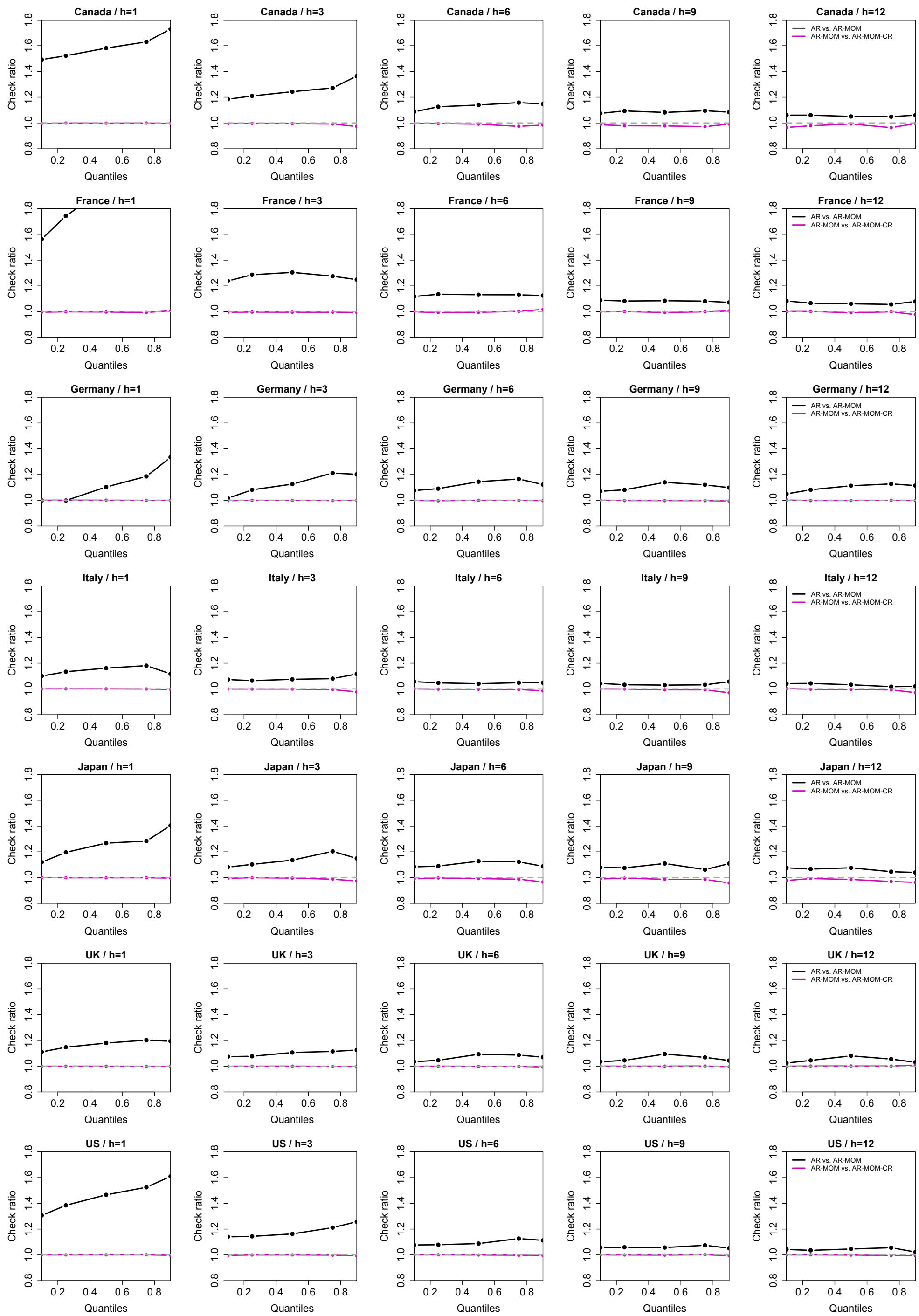

Figure 2: Quantile regression results for a rolling estimation window (RMSFE ratios)