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CLIMATE RISKS AND PREDICTABILITY OF COMMODITY RETURNS AND VOLATILITY: EVIDENCE FROM OVER 750 YEARS OF DATA

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We analyze whether metrics of climate risks, as captured primarily by changes in temperature anomaly and its stochastic volatility (SV), can predict returns and volatility of 25 commodities, covering the overall historical period of 1258 to 2021. To this end, we apply a higher-order nonparametric causality-in-quantiles test to not only uncover potential in-sample predictability in the entire conditional distribution of commodity returns and volatility but also to account for nonlinearity and structural breaks which exist between commodity returns and the metrics of climate risks. We find that, unlike in the misspecified linear Granger causality tests, climate risks do predict commodity returns and volatility, though the impact on the latter is stronger, in terms of the coverage of the conditional distribution. Insights from our findings can benefit academics, investors, and policymakers in their decision-making.

Keywords: Climate risks; commodities; returns and volatility predictions; higher-order nonparametric causality-in-quantiles test.

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1. Introduction

The role of climate risks, as captured by changes/growth in temperature and precipitation and their respective volatilities, as well as the measures of the El Niño Southern Oscillation (ENSO), in predicting movements of agricultural commodity prices has been analyzed by a large number of studies (see for example, Brunner, 2002, Ubilava (2012a, 2012b, 2014, 2017), Ubilava and Holt (2013), Cashin *et al.* (2017), Bastianin *et al.* (2018), Atems *et al.* (2020), Atems and Sardar (2021), Makkonen *et al.* (2021), Bonato *et al.* (2023) and Gupta and Pierdzioch (2023)).[1] More recently, however, the focus has also been on the impact of climate change-related events on the first- and second-moment of prices and/or returns of nonagricultural energy-based commodities, as well as that of precious metals (Ubilava, 2018; Qin *et al.*, 2020; Balcilar *et al.*, 2018b; Bouri *et al.*, 2021; Gupta and Pierdzioch, 2021, 2022; Cepni *et al.*, 2022; Demirer *et al.*, 2022; Salisu *et al.*, 2022; Guo *et al.*, 2023). In other words, the focus is now basically on the entire commodity sector, due to the emergence of the same alternative investment options to standard financial assets, in the wake of its financialization over the last two decades, and especially post the global financial crisis (Tang and Xiong, 2012; Adams and Gluck, 2015; Hamilton and Wu, 2015; Bonato, 2019), thus making it important to analyze the drivers of its returns and volatility from the perspective of investors aiming to make optimal portfolio allocation decisions. In this regard, note that studies (see, Engle *et al.* (2020), Battiston *et al.* (2021), Giglio *et al.* (2021) and Bonato *et al.* (2022)) have indicated that climate change impacts various traditional asset classes (currencies, equities, fixed-income securities, real estate, and even financial institutions), with the commodity market channelling climate risks into the stress of the entire financial system Flori *et al.* (2021), Chen *et al.* (2023), Dong and Liu (2023), Sun *et al.* (2023). Besides this, commodity price movements are known to lead to macroeconomic variables, such as output and inflation (see Liu and Serletis (2022) for a detailed review of this literature), making its predictability important for policymakers in terms of the design of appropriate policy responses.

At the same time, from a theoretical perspective, the emphasis in recent research on analyzing the impact of climate risks on the commodity market as a whole should not come as a surprise. This is because climate risks serve as proxies for rare disaster events (Donadelli *et al.*, 2017, 2021a,b, 2022), and several theories link rare disaster concerns to the causation of commodity-price returns and volatility (Demirer *et al.*, 2018). First, rare disaster risks affect consumption and production decisions (Rietz, 1988; Lucas, 2003; Barro, 2006), policies (Niemann and Pichler, 2011), and global trade (Ready *et al.*, 2017). Hence, by affecting the behavior of agents and macroeconomic policies, the demand and supply of commodities will be affected by rare

[1]In this regard, also see the works of Lokonon *et al.* (2019), Calvin *et al.* (2020), McFadden and Miranowski (2020), Barve *et al.* (2021) and Corato and Ginbo (2021) for agricultural commodities and Moore *et al.* (2021) for the impacts of climate change on fisheries.

disaster risks, thus, causing fluctuations in commodity prices. Second, the beliefs and preferences of investors regarding rare disasters have to be taken into account. As indicated by Chen *et al.* (2012), rare disaster events obscure both the probability and severity of disasters and lead to greater disagreements about disaster risk. Accordingly, concerns of rare disasters are associated with a subsequent impact on commodity-price movements. Third, rare disaster concerns are known to lead to potential economic transformation, which, in turn, is likely to affect commodity markets. Kalemli-Ozcan *et al.* (2003) argue that rare disaster risk plays an important role in determining industrial specialization due to the risk-sharing intention of various industries. As the economic condition of industries changes, there will be a corresponding impact on commodity prices (Zhang, 2021). Finally, a common view is that risk is a type of uncertainty that rational agents face when making their decisions, where even when agents can contemplate possible states of nature and have some idea of their likelihood, the exact distribution is not known (Knight, 1921). Hence, the rise in uncertainty resulting from rare disaster risks associated with climate change is likely to make the path of future aggregate demand and aggregate production less predictable. Facing the enhanced uncertainty emanating from this more intense unpredictability, risk-averse commodity producers will prefer to hold physical inventory when facing uncertain aggregate demand conditions. Increases in inventories, in turn, are likely to increase the convenience yield for holding physical inventory and eventually will amplify the variance of returns of commodity prices (Bakas and Triantafyllou, 2018, 2020). In other words, the causal effect of climate risks on returns and volatility of commodity prices can originate from multiple theoretical routes.

In light of the burgeoning literature on the effect of climate risks on commodity price movements, given its importance, and also the well-established underlying theoretical channels defining this nexus, our objective is to extend the empirical literature from a historical standpoint. Specifically, unlike the existing papers on the predictive value of climate risks for commodity returns and volatility based on post-World War II data (in fact, more precisely, since the 1960s), our analysis covers the longest data sample available on 25 important commodities covering the overall annual period of 1258 to 2021. In particular, we analyze the effects of both changes in global temperature and its volatility as main predictors in accordance with the current literature on measuring risks of climate change (with the ENSO as an alternative metric), in predicting the returns and volatilities of Aluminum, Banana, Beef, Cocoa, Coal, Coffee, Copper, Cotton, Gold, Hide, Jute, Lamb, Lead, Nickel, Oil, Pig Iron, Rice, Silver, Sugar, Tea, Tin, Tobacco, Wheat, Wool, and Zinc. The decision to look at such a long sample period is due to several reasons: First, global warming has evolved slowly over centuries and, hence, ideally requires long data samples. Second, such prolonged data spans allow correct inferences of the predictability of climate risks on commodity markets to be drawn by avoiding a sample-selection bias, as the data set corresponds to the longest available price history of these 25 commodities, i.e., their entire evolution process.

The existing literature cited above suggests that climate risks are nonlinearly related to commodity prices and that the relationships are subjected to structural breaks. With us statistically validating these claims, which should not come as a surprise in light of the length of the historical sample period that we study, we would need an econometric approach that is robust to the violation of linearity and the existence of regime changes, while providing a predictability test of both returns and volatility within a unified framework. In this regard, we resort to the *k*th-order nonparametric causality-in-quantiles test proposed by Balcilar *et al.* (2018a), which has several novelties:[2] First, the test is robust to functional misspecification errors and can detect general dependence between time series, i.e., it is unaffected by the existence of nonlinearity and structural breaks that we detect in our data set. Second, the test statistic does not only test for causality-in-mean, but it also tests for predictability that may exist in the tail area of the joint distribution of the series, which too is important in our context given the nonnormality of the commodity returns that we investigate. Third, the test easily lends itself to test for causality-in-variance, as captured by squared returns, which, in turn, renders it possible to test for second-moment causality due to climate risks, since, at times, causality-in-conditional-mean (first-moment) may not exist, but there may be second-order quantiles-based predictability. We must emphasize that in this paper we concentrate on causality running from climate risks to returns and volatility using a nonparametric higher-order test, and hence basically deal with in-sample predictability and not out-of-sample forecasting.

To the best of our knowledge, this is the first paper to analyze the quantiles-based predictability of climate risks on returns and volatility of commodities, based on data covering eight centuries (from 1258 to 2021) based on over 750 years of data. The remainder of this paper is organized as follows: Section 2 outlines the methodology, while Sec. 3 discusses the data. Section 4 is devoted to the empirical results, with Sec. 5 concluding this paper.

2. Methodology

We use the quantile-in-causality test developed by Balcilar *et al.* (2018a). This is a nonparametric, nonlinear causality test based on the work by Nishiyama *et al.* (2011) and Jeong *et al.* (2012). Let y_t denote the real log returns of various commodities, while x_t denotes the specific climate risks variable, with details of both dependent and independent variables described in the data section below.

Now, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{(y_t|\cdot)}(y_t| \bullet)$, which denotes the conditional distribution of y_t given $\bullet$. If we define $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we obtain that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with

[2]Not surprisingly, besides commodities, this test has been applied to predictability of returns and volatility of various types of assets namely, equities, bonds, currencies, real estate, etc., emanating from wide array of predictors (see for example, Bahloul *et al.*, 2018 and Balcilar *et al.* (2018b, 2019, 2020, 2021a)) and our description of the technical details of the test draws on this earlier research.

probability one. This allows us to test the hypotheses of (non)causality in the θth quantile with the following:

$$H_0 : P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1, \tag{1}$$

$$H_1 : P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1. \tag{2}$$

The feasible kernel-based test statistic, as shown by Jeong *et al.* (2012), has the following formulation:

$$\widehat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1,\, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right)\hat{\varepsilon}_t \hat{\varepsilon}_s, \tag{3}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, with $\mathbf{1}\{\bullet\}$ the indicator function and $\hat{Q}_\theta(Y_{t-1})$ an estimate of the θth conditional quantile. We use the *Nadarya–Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$, which is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1,\, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)\mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,\, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)}, \tag{4}$$

where $L(\bullet)$ denotes the kernel function.

As mentioned, Balcilar *et al.* (2018a) extended the framework proposed by Jeong *et al.* (2012), which in turn is based on the work by Nishiyama *et al.* (2011), to the kth moment which allows us to test causality at higher moments. In our case, we focus on $k = 1$ and $k = 2$, and examine the causal relationship between climate risk and commodity returns and its volatility. In general, causality at the Kth moment is tested via the null and alternative hypotheses given by

$$H_0 : P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1, \quad k = 1, 2, \ldots, K, \tag{5}$$

$$H_1 : P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1, \quad k = 1, 2, \ldots, K. \tag{6}$$

Replacing y_t in Eqs. (3) and (4) with y_t^2 yields a special case: the causality-in-variance test. Balcilar *et al.* (2018a) point out that a rescaled version of $\widehat{J}_T$ has the standard normal distribution. With a sequential testing approach, we can test for causality at each moment independent of the results of other moments, therefore, failing to reject the test for $k = 1$ does not automatically lead to no-causality in the second moment (i.e., noncausality in means does not imply that there is no causality in variances).

There are three key parameters required for the empirical implementation of the higher-order causality testing via quantiles: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We determine h by the leave-one-out least-squares cross-validation. We use a lag order based on the Schwarz Information Criterion (SIC), while we use Gaussian kernels for $K(\cdot)$ and $L(\cdot)$.

3. Data

Risks associated with climate change or more specifically, global warming in this regard, are based on global temperature anomaly (in degrees Celsius) with respect to the May–April annual average over 1961–1990. The temperature anomaly data until 2019 (which is available from 1 AD) is obtained from Hawkins (2020),[3] and then updated for the years 2020 and 2021 from the National Oceanic and Atmospheric Administration (NOAA).[4] We then take the first difference of temperature anomaly to obtain DT and estimate the stochastic volatility (SV) model of.[5] In addition, we also estimate a best-fitting Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, i.e., Glosten–Jagannathan–Runkle (GJR-GARCH)[6] of Glosten *et al.* (1993) on this data. In this way, we derive two alternative metrics of conditional volatility of DT, which we denote as SV and GARCH, respectively. In the process, we obtain the first- and second-moment associated with climate change.

Following the existing literature, we also rely on the ENSO as a measure of climate risks, with the data obtained from Gergis and Fowler (2006) and Climate History,[7] both available from 1525. The ENSO, characterized by El Niño and La Niña events,[8] are captured with a dummy variable that takes the value 1 when either of these two events was identified and zero otherwise.

The data on real prices[9] of 24 commodities compiled by Harvey *et al.* (2017) until 2014 forms the main basis of our dataset, which we then update with comparable data from Bloomberg until 2021. The only exception in this regard is the data on the gold price, which is derived from MeasuringWorth.com,[10] and is available from 1257.[11]

[3]https://web.archive.org/web/20200202220240/https://www.climate-lab-book.ac.uk/2020/2019-years/.

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

[5]Letting denote change in global temperature anomaly by: $y = (y_1, y_2, \dots, y_T)'$, the SV model is specified as: $y_t = e^{h_t/2}\varepsilon_t$, with $h_t = \mu + \psi(h_{t-1} - \mu) + \sigma v_t$, where the i.i.d. standard normal innovations ε_t and v_s are by assumption independent for $v, s \in \{1, \dots, T\}$. The unobserved process $h = (h_0, h_1, \dots, h_T)$ 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., $h_0|\mu, \psi, \sigma \sim \mathcal{N}(\mu, \sigma^2/(1 - \psi^2))$. The noncentered parameterization of the model is given by: $y_t \sim \mathcal{N}(0, \omega e^{\sigma \tilde{h}_t})$, with $\tilde{h}_t = \psi\tilde{h}_{t-1} + v_t, v_t \sim \mathcal{N}(0, 1)$, 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 SV model can be obtained from the authors upon request.

[6]GJR-GARCH specification is as follows: $y_t = \mu + \rho y_{t-1} + \varepsilon_t$, and $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-1}^2 d_{t-1} + \beta_0 h_{t-1}$, where y_t represents the change in global temperature anomaly, and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (α_0), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$ if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The shocks have an asymmetric impact on conditional variance if α_2 is statistically significant. Detailed estimation results for the GJR-GARCH model can be obtained from the authors upon request.

[7]Data is available for download from: https://sites.google.com/site/medievalwarmperiod/Home/historic-el-nino-events.

[8]It is well established that the ENSO, an irregularly periodic variation in winds and sea surface temperatures over the tropical eastern Pacific Ocean, tends to influence the climate of much of the tropics and subtropics (Trenberth *et al.*, 2007). The warming phase of sea temperature is known as El Niño and the corresponding cooling phase as La Niña. Each of these two phases can last several months, and usually they occur every few years with intensities varying per phase. Understandably, the ENSO is an important source of inter-annual variability in weather and climate patterns in many parts of the world (Shabbar and Khandekar, 1996).

[9]The nominal prices in British pound sterling are deflated by a price index of manufacturers.

[10]https://www.measuringworth.com/.

[11]The nominal price of gold was deflated with the consumer price index of the UK (derived from Bank of England's: "A millennium of macroeconomic data for the UK" till 2016, and then for the remainder of the period, we rely on the Main Economic Indicators (MEI) of the Organisation for Economic Co-operation and Development (OECD)), as the price index for manufacturers used to deflate the other commodities do not go beyond 1650.

Besides this, eleven series begin in the 17th century (Beef, Coal, Cotton, Lamb, Lead, Rice, Silver, Sugar, Tea, Wheat, and Wool), three series begin in the 18th century (Coffee, Tobacco, and Pig Iron), eight series begin in the 19th century (Aluminum, Cocoa, Copper, Hide, Nickel, Oil, Tin, and Zinc), and two starts from 1900 (Banana and Jute). We then work with the real log returns to account for the nonstationary nature of the price data. Stationarity of the time series being analyzed is required to draw appropriate inferences from the *k*th order nonparametric causality-in-quantiles test.

In line with the recent literature on measuring climate risks, our main focus is the predictors DT and SV. We provide the summary statistics of data associated with the real log returns of the commodities, along with DT and SV, in Table A.1 at the end of this paper (Appendix A). The nonnormality of the commodity returns tends to provide a preliminary motivation to use a quantiles-based approach to predictability in our context. The data of the relevant variables have also been plotted in Fig. A.1 in Appendix A.

4. Results

Before discussing our findings of the quantile-based test, we consider the linear Granger causality tests as given in Table 1 for the sake of completeness and comparability. With the exception of the Gold-SV and Oil-SV bivariate models, we find no evidence of Granger causality from climate risks to returns of commodities.

We then proceed to test for misspecification as a possible explanation for non-causality in the linear model. Specifically, we first test for the presence of nonlinearity using the Brock *et al.* (1996, BDS) test applied to the residuals recovered from the Granger causality model. As reported in Table A.2 (Appendix A), we reject the null hypothesis of *i.i.d.* residuals at various dimensions (m) at various significance levels for most of the commodities, with the only exception being Jute. This indicates the presence of uncaptured nonlinearity in the relationship between commodity returns and climate risks. In order to test for the presence of possible structural breaks, we use the powerful UDmax and WDmax tests of Bai and Perron (2003) and report the results in Table A.3. There are various structural breaks for a majority of the commodities, and, importantly, Jute has structural breaks under both DT and SV, indicating that there is evidence that all the equations for the commodities were misspecified in the linear Granger causality test and that a quantile-based test is appropriate in our context.

We summarize the results of the causality-in-mean results (i.e., on commodity returns, due to DT and SV) in Tables 2 and 3. We find a causal relationship between commodities and climate risks when it is measured by DT for a broad range of quantiles (in general ranging between $\tau = 0.15$–0.80), except for Banana, Beef, Wheat, and Zinc, where predictability is limited to around the median, and for Jute where there is no evidence of a causal relationship. The strongest effects (in terms of significance) are concentrated around the median (i.e., for τ between 0.40 to 0.60) for Aluminum, Beef, Coal, Coffee, Copper, Cotton, Gold, Tea, Tin, Tobacco, and Wool. As far

Table 1. Linear Granger causality test results.

	DT	SV
Aluminum	2.316 (0.314)	0.973 (0.808)
Banana	3.806 (0.283)	0.468 (0.791)
Beef	1.087 (0.581)	2.067 (0.559)
Coal	0.752 (0.687)	1.741 (0.628)
Cocoa	0.865 (0.649)	2.224 (0.527)
Coffee	6.783 (0.034)	0.150 (0.985)
Copper	2.174 (0.537)	0.255 (0.880)
Cotton	1.349 (0.509)	0.752 (0.861)
Gold	2.604 (0.457)	10.658 (0.014)
Hide	4.197 (0.123)	3.408 (0.333)
Iron	0.633 (0.729)	0.105 (0.949)
Jute	0.831 (0.660)	0.084 (0.959)
Lamb	1.586 (0.663)	0.837 (0.841)
Lead	0.441 (0.802)	0.175 (0.982)
Nickel	4.789 (0.188)	0.920 (0.631)
Oil	2.618 (0.106)	7.372 (0.025)
Rice	1.663 (0.436)	1.050 (0.789)
Silver	0.146 (0.930)	5.296 (0.151)
Sugar	3.198 (0.202)	0.907 (0.824)
Tea	6.068 (0.048)	0.510 (0.917)
Tin	2.837 (0.242)	2.716 (0.438)
Tobacco	5.414 (0.067)	1.798 (0.615)
Wheat	2.031 (0.362)	0.791 (0.852)
Wool	3.083 (0.214)	1.782 (0.619)
Zinc	1.285 (0.526)	0.739 (0.691)

Notes: The χ^2 test statistics are given for the equation tested under SIC lags, while the p-values are given in parenthesis.

as the strongest effects of Banana, Cocoa, Hide, Iron, Lamb, Oil, and Wheat are concerned, we identify them at quantiles below 0.40, while for Lead, Rice, Silver, Sugar, and Zinc, the strongest effect can be found above $\tau = 0.60$. In general, barring the case of Jute, temperature changes do tend to cause commodity returns, though there is heterogeneity in terms of the quantiles where causality holds, i.e., whether markets are bearish (lower quantiles), normal (around the median), or bullish (higher quantiles). Interestingly, extreme quantiles capturing exceptionally low or high conditional returns are not predictable by the temperature changes (see Tables A4 and A5 where we present the causality-in-quantile results for different measures of climate uncertainty on commodity returns).

Considering SV as the measure of climate risk, the causal relationships are more focused on certain parts of their conditional distributions, with Aluminum, Cocoa, Coffee, Cotton, Gold, Lead, Nickel, Oil, Rice, Silver, Sugar, Tin, Tea, Tobacco, and Wool showing evidence for a broader range of quantiles covering bearish, normal, and bullish phases. Banana's

Table 2. *k*th order causality-in-quantiles test results on commodity returns due to DT.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	1.178	0.741	1.377	1.326	1.139	1.126	0.884	1.623	1.439	1.066	1.197	0.601	1.282
0.10	1.720*	1.328	1.943*	1.481	2.072**	1.624	1.471	2.250**	1.864*	1.479	1.330	0.479	1.688*
0.15	2.113**	1.534	1.597	1.749*	2.352**	1.931*	1.702*	3.048***	2.435**	2.338**	1.657*	0.824	1.837*
0.20	2.109**	2.050**	1.579	1.960**	2.800***	2.249**	1.890*	3.342***	2.689***	2.159**	2.134**	0.813	2.467**
0.25	2.165**	2.184**	1.555	2.471**	2.923***	2.535**	2.217**	3.812***	3.116***	2.566**	2.721***	1.109	2.643***
0.30	2.239**	2.409**	1.644	2.906***	3.300***	2.424**	2.136**	3.943***	3.222***	2.825***	3.429***	1.130	2.852***
0.35	2.335**	2.981***	2.125**	3.124***	3.346***	2.333**	2.463**	4.079***	3.656***	2.350**	3.239***	1.256	2.746***
0.40	2.480**	2.497**	2.101**	3.120***	3.307***	2.290**	2.657***	4.232***	4.258***	2.686***	3.064***	1.136	2.384**
0.45	2.313**	2.758***	2.396**	3.347***	2.789***	2.590***	2.241**	4.364***	3.852***	2.381**	3.002***	1.069	2.308**
0.50	2.326**	2.256**	2.447**	3.467***	2.529**	2.717***	2.108**	4.545***	4.380***	2.167**	2.822***	1.231	2.514**
0.55	2.639***	2.411**	2.530**	3.098***	2.628***	3.449***	2.199**	4.431***	4.524***	1.731*	2.919***	0.874	2.192**
0.60	2.934***	2.522**	1.942*	2.816***	2.429**	3.871***	2.398**	4.005***	4.381***	1.942*	2.506**	0.779	2.168**
0.65	2.299**	1.971**	1.767*	2.627***	2.452**	3.592***	2.278**	4.040***	4.518***	2.261**	2.261**	0.893	2.013**
0.70	2.389**	1.486	1.619	2.458**	2.433**	2.665***	2.424**	4.171***	4.146***	1.974**	2.616***	0.890	1.676*
0.75	2.437**	1.668*	1.407	2.836***	2.080**	2.403**	1.985**	3.839***	4.393***	2.078**	2.55**	0.823	1.795*
0.80	2.170**	1.338	1.289	2.831***	1.931*	2.041**	2.149**	3.901***	3.704***	1.683*	2.633***	0.986	1.898*
0.85	1.622	1.020	1.502	2.533**	1.849*	1.848*	1.701*	3.235***	3.146***	1.526	2.243**	0.728	1.736*
0.90	1.357	0.912	1.132	1.829*	1.295	1.825*	1.277	2.167**	2.521**	1.264	1.476	0.817	1.640
0.95	0.982	0.425	0.937	1.138	0.914	1.432	1.061	1.495	1.512	0.968	1.025	0.345	1.204

Table 2. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	1.222	1.011	1.291	1.014	1.608	1.836*	1.167	1.824*	1.368	1.005	0.847	0.683
0.10	1.701*	1.470	1.688*	1.171	2.323**	2.925***	1.525	2.610***	1.585	1.386	1.478	1.059
0.15	2.047**	2.366**	2.394**	1.669*	2.629***	2.730***	1.969**	3.107***	1.879*	1.772*	1.997**	1.224
0.20	2.551**	2.346**	2.630***	2.024**	2.747***	2.852***	2.226**	3.359***	1.866*	1.602	2.483**	1.370
0.25	2.091**	2.489**	2.636***	2.097**	2.602***	2.681***	2.174**	3.780***	2.128**	2.154**	2.416**	1.764*
0.30	2.098**	2.795***	2.680***	2.115**	2.883***	2.747***	2.434**	3.600***	2.276**	2.278**	2.451**	1.853*
0.35	2.197**	2.580***	2.935***	2.225**	3.039***	2.712***	2.406**	3.801***	2.521**	1.978**	2.207**	2.126**
0.40	2.184**	2.913***	2.782***	2.054**	3.276***	2.539**	2.252**	4.054***	2.544**	1.746*	2.810***	2.324**
0.45	2.038**	3.069***	2.871***	2.071**	3.294***	2.858***	2.448**	4.065***	2.855***	1.793*	2.501**	1.997**
0.50	2.075**	3.090***	2.804***	2.073**	3.063***	2.730***	2.681***	4.383***	2.972***	1.942*	2.374**	1.983**
0.55	2.063**	2.957***	2.922***	2.374**	3.332***	2.856***	3.056***	4.253***	3.495***	2.101**	2.397**	2.216**
0.60	2.561**	2.811***	2.532**	2.538**	3.687***	2.784***	3.801***	4.421***	3.313***	1.920*	2.167**	1.954*
0.65	3.114***	2.680***	2.779***	2.344**	3.369***	2.849***	2.891***	4.176***	3.381***	1.633	2.193**	2.467**
0.70	3.151***	2.470**	2.718***	2.282**	3.591***	3.050***	2.984***	3.740***	3.009***	1.770*	2.529**	2.050**
0.75	3.556***	2.681***	2.655***	2.771***	3.868***	3.531***	2.503**	3.659***	3.170***	1.118	2.422**	1.219
0.80	3.621***	2.459**	2.545**	1.883*	3.615***	3.297***	2.618***	3.413***	3.231***	1.124	2.320**	1.265
0.85	2.909***	1.982**	2.090**	1.606	3.351***	2.759***	2.278**	2.919***	2.871***	0.914	1.717*	1.123
0.90	2.629***	1.837*	1.506	1.532	2.299**	2.188**	1.888*	2.367**	1.933*	0.802	1.545	0.904
0.95	1.226	0.999	1.050	0.750	1.327	1.181	0.982	1.685*	0.948	0.544	1.008	0.482

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to commodity returns for a particular quantile.

Table 3. *k*th order causality-in-quantiles test results on commodity returns due to SV.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	1.176	0.775	1.397	0.945	0.759	1.241	0.734	1.083	0.828	0.889	0.864	0.353	0.937
0.10	1.515	1.038	1.561	1.317	1.411	1.392	1.116	1.802*	1.058	1.412	1.014	0.612	1.357
0.15	1.841*	0.954	1.273	1.751*	2.040**	2.054**	1.442	2.135**	1.341	2.111**	1.337	0.791	1.660*
0.20	2.449**	1.222	1.655*	2.298**	2.778***	2.467**	1.662*	2.203**	1.387	1.989**	1.398	0.813	2.097**
0.25	2.623***	1.215	1.858*	1.943*	2.784***	2.141**	2.089**	2.359**	2.138**	2.580***	2.063**	0.967	1.927*
0.30	2.407**	1.440	1.768*	2.398**	3.591***	2.274**	2.229**	2.110**	2.203**	2.387**	2.005**	0.838	1.911*
0.35	2.715***	1.537	1.279	2.894***	4.107***	2.149**	1.824*	2.654***	2.298**	2.190**	1.817*	0.779	1.935*
0.40	2.324**	1.647*	1.091	2.301**	3.061***	1.804*	2.035**	3.285***	2.360**	1.636	1.621	0.664	1.632
0.45	2.338**	1.598	1.484	2.076**	2.691***	1.684*	1.394	3.705***	2.566**	2.040**	1.354	0.835	1.936*
0.50	2.321**	1.797*	1.558	1.930*	2.526**	1.566	1.214	3.510***	2.922***	1.794*	1.413	0.856	1.848*
0.55	2.336**	2.154**	1.989**	1.223	2.438**	1.907*	1.069	3.798***	3.027***	1.411	1.553	0.816	2.200**
0.60	1.976**	2.233**	1.708*	1.135	2.232**	2.180**	0.992	3.402***	2.773***	1.471	1.576	0.715	2.207**
0.65	1.860*	1.561	1.565	1.326	2.145**	2.435**	1.062	2.677***	2.815***	1.509	1.731*	0.801	2.008**
0.70	2.216**	1.542	1.735*	1.262	2.274**	1.614	1.205	2.591***	2.393**	1.564	1.704*	0.768	1.632
0.75	2.201**	1.421	2.055**	1.846*	2.253**	1.899*	1.512	2.252**	2.152**	1.973**	1.955*	0.676	1.449
0.80	2.052**	1.162	3.295***	2.113**	2.027**	2.204**	1.326	2.125**	1.895*	1.580	1.954*	0.493	1.576
0.85	1.697*	1.080	4.061***	1.685*	1.794*	2.457**	1.278	1.754*	1.929*	1.259	2.024**	0.521	1.447
0.90	1.262	0.827	2.581***	1.419	1.325	2.582***	1.148	1.701*	1.531	1.101	1.528	0.320	1.854*
0.95	0.766	0.622	1.28	1.31	0.686	1.240	0.619	0.954	1.128	0.527	0.991	0.325	1.197

Table 3. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	1.017	0.955	1.129	0.755	1.696*	1.856*	0.968	1.441	0.859	0.716	0.721	0.592
0.10	1.599	1.104	1.522	1.286	2.060**	3.004***	1.463	2.081**	1.635	1.123	1.263	1.007
0.15	2.185**	1.753*	1.768*	1.829*	1.786*	2.644***	1.171	2.294**	1.354	1.272	1.450	1.188
0.20	2.124**	2.112**	2.127**	1.693*	1.777*	2.870***	1.396	2.370**	1.76*	1.314	1.949*	1.280
0.25	1.834*	2.329**	2.490**	2.405**	1.713*	2.547**	1.949*	2.578***	2.387**	1.211	2.168**	1.250
0.30	1.629	2.205**	2.629***	2.362**	1.931*	2.309**	2.028**	2.593***	2.630***	1.506	1.783*	1.256
0.35	1.650*	2.990***	2.444**	1.843*	1.897*	2.304**	2.255**	2.926***	2.307**	1.129	1.890*	1.139
0.40	1.714*	2.644***	2.126**	2.009**	2.037**	2.026**	2.131**	3.164***	1.667*	0.822	2.095**	1.574
0.45	1.803*	2.034**	1.884*	1.969**	2.001**	2.199**	2.097**	3.390***	1.863*	0.779	1.806*	1.132
0.50	1.598	1.997**	1.868*	2.103**	1.832*	2.551**	2.399**	3.356***	1.724*	0.957	1.968**	1.145
0.55	1.874*	1.773*	1.846*	2.069**	1.595	2.394**	2.359**	3.187***	1.619	1.120	1.962**	1.048
0.60	1.963**	1.812*	2.378**	2.425**	1.583	2.307**	2.526**	3.283***	2.173**	0.806	1.627	0.836
0.65	2.547**	1.727*	2.766***	2.692***	1.800*	2.941***	2.683***	3.223***	2.522**	0.825	1.821*	1.003
0.70	2.221**	1.609	3.156***	2.935***	1.777*	3.659***	2.396**	2.936***	2.411**	0.659	2.136**	1.101
0.75	2.830***	1.873*	2.904***	3.302***	1.772*	3.659***	2.086**	2.937***	2.809***	0.647	2.011**	1.051
0.80	2.918***	2.303**	2.400**	2.322**	1.990**	3.554***	1.660*	2.544**	2.250**	0.797	1.574	1.110
0.85	2.778***	2.258**	1.907*	1.713*	2.300**	3.778***	2.085**	2.270**	1.978**	0.653	1.063	1.110
0.90	3.198***	1.583	1.317	1.207	1.964**	2.824***	1.437	1.978**	1.580	0.748	0.989	1.086
0.95	1.422	0.803	0.904	0.581	1.189	1.911*	1.169	1.279	0.968	0.424	0.834	0.448

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to commodity returns for a particular quantile.

relationship with SV as the climate-risk measure is focused around the median, while Beef is more focused around the upper half of its conditional distribution, with the opposite being true for Coal, Copper, and Hide. For Iron, we find a significant causal relationship in the upper and lower quantiles of its conditional distribution (but not at the extreme ends), while for Lamb, we observe the same between $\tau = 0.15$–0.65. The strongest effects for Banana, Cotton, Gold, Lamb, and Tin are around the median (i.e., between the 40th and 60th quantiles), while Aluminum, Coal, Cocoa, Copper, Hide, Iron, and Nickel have the strongest impact below the 40th quantile (i.e., bearish state). For Beef, Coffee, Lead, Oil, Rice, Silver, Sugar, Tea, Tobacco, and Wool strong predictability is above the 60th quantile, or in its bullish state. Just as with DT, its conditional volatility too, as captured by SV, tends to predict commodity returns, barring the extreme conditional quantiles.

The causality-in-variances results, i.e., for the volatility of commodity returns, as captured by squared returns due to DT and SV, are given in Tables 4 and 5. We find that both measures of climate risks have much more significant causal impacts on commodity-returns volatility than on returns themselves, with significant results for nearly the entire conditional distribution for all commodities. The strongest effect, in terms of the strength of statistical significance, for all the commodities, lies between the 40th and 60th quantiles, except for Iron ($\tau = 0.65$) with DT as the climate risk measure, and Wheat ($\tau = 0.70$) and Wool ($\tau = 0.65$) for SV (see Tables A6 and A7 where we present the causality-in-quantile results for different measures of climate uncertainty on the volatility of commodity returns).

In sum, the strength of the predictive relationship between the climate risk metrics with commodity returns and volatility could be summarized by an inverse u-shape over their respective conditional distributions.

The results for the volatility of DT derived from the GJR-GARCH, as well as the predictability of the ENSO, on both commodity returns and volatility, are reported at the end of this paper (Appendix A). As with SV, the GARCH results are found to have stronger predictive content for volatility, than the first-moment of commodity returns. As far as the ENSO[12] is concerned, we do not necessarily observe the same overwhelming evidence of causality as under DT and SV, with its effects focused more on the tails than the median of the conditional distributions. These findings seem to conform with the recent trend in the climate-risks/commodity-market movements literature, whereby global changes in temperature and its volatility through SV models are considered to be more reliable metrics of rare-disaster concerns involving global warming and climate change.

In summary, we find statistically significant predictive relationships from robust measures of climate risks to the first- and second moments of commodity-price movements. These effects are commodity-specific when looking at commodity returns and tend to become weaker at the extreme ends of the market, however, for their

[12]When we split consider the two parts of the ENSO cycle (El Niño and La Niña), we find that the El Niño cycle exhibits stronger effects than La Niña on commodity returns, while the effect on volatility is similar. These results for Gold, despite using lower frequency data for a much longer time period, are similar to that reported in Salisu *et al.* (2022).

Table 4. *k*th order causality-in-quantiles test results on squared commodity returns (volatility) due to DT.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	1.867*	1.558	2.810***	2.794***	1.923*	2.276**	2.113**	3.264***	4.308***	2.364**	2.104**	1.503	2.965***
0.10	2.610***	2.121**	3.660***	3.716***	3.118***	3.045***	3.052***	4.114***	5.930***	2.971***	2.927***	1.987**	4.217***
0.15	3.103***	2.703***	4.404***	4.267***	4.203***	3.694***	3.233***	4.785***	7.014***	3.414***	3.480***	2.373**	4.808***
0.20	3.426***	2.966***	5.046***	4.822***	4.581***	4.190***	3.465***	5.067***	7.821***	3.684***	3.687***	2.574**	5.297***
0.25	3.765***	3.015***	5.433***	5.164***	4.781***	4.690***	3.803***	5.551***	8.414***	4.566***	3.984***	3.050***	5.651***
0.30	3.865***	3.017***	5.710***	5.482***	4.728***	4.942***	4.107***	6.018***	8.881***	4.538***	4.166***	3.163***	5.957***
0.35	4.026***	2.986***	5.956***	5.834***	5.013***	5.021***	4.111***	6.128***	9.215***	4.643***	4.064***	3.201***	6.305***
0.40	4.184***	3.246***	5.836***	5.956***	4.933***	4.909***	4.400***	6.266***	9.457***	4.558***	4.341***	3.277***	6.531***
0.45	4.136***	3.356***	5.929***	5.967***	5.014***	4.985***	4.583***	6.316***	9.667***	4.707***	4.476***	3.079***	6.612***
0.50	4.023***	3.377***	6.035***	6.049***	4.995***	4.960***	5.073***	6.320***	9.682***	4.754***	4.521***	3.135***	6.507***
0.55	3.932***	3.345***	6.338***	5.946***	4.874***	4.950***	4.795***	6.134***	9.612***	4.845***	4.403***	3.166***	6.411***
0.60	3.926***	3.419***	6.231***	5.891***	4.737***	5.081***	4.572***	6.048***	9.469***	4.613***	4.591***	3.069***	6.526***
0.65	3.846***	3.405***	5.989***	5.793***	4.501***	4.945***	4.628***	5.907***	9.204***	4.387***	4.686***	2.929***	6.425***
0.70	3.648***	2.996***	5.708***	5.524***	4.564***	4.587***	4.300***	5.650***	8.835***	4.414***	4.146***	2.832***	6.120***
0.75	3.648***	2.661***	5.274***	5.244***	4.213***	4.465***	3.972***	5.135***	8.364***	4.034***	3.864***	2.847***	5.742***
0.80	3.484***	2.580***	4.799***	4.938***	3.932***	4.221***	3.362***	4.813***	7.654***	3.588***	3.634***	2.433**	5.132***
0.85	3.211***	2.153**	4.332***	4.193***	3.437***	3.636***	3.045***	4.351***	6.868***	3.172***	3.079***	2.450**	4.453***
0.90	2.463**	1.709*	3.590***	3.521***	2.739***	3.072***	2.318**	3.629***	5.705***	2.722***	2.662***	1.962**	3.749***
0.95	1.636	1.203	2.442**	2.552**	1.745*	2.166**	1.534	2.664***	4.188***	1.733*	1.765*	1.295	2.706***

Table 4. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	2.757***	2.242**	2.159**	2.512**	2.402**	2.976***	2.739***	2.141**	2.146**	2.197**	2.550**	1.837*
0.10	3.498***	2.850***	2.960***	3.543***	3.326***	3.915***	3.674***	2.839***	3.021***	3.150***	3.504***	2.415**
0.15	4.207***	3.037***	3.290***	4.206***	3.965***	4.796***	4.250***	3.542***	3.681***	3.753***	4.247***	3.034***
0.20	4.820***	3.510***	3.655***	4.813***	4.451***	5.190***	4.617***	3.896***	4.093***	4.227***	4.691***	3.316***
0.25	5.369***	3.837***	4.004***	5.261***	4.798***	5.592***	5.131***	4.074***	4.565***	4.338***	5.022***	3.467***
0.30	5.525***	3.936***	4.206***	5.553***	5.228***	5.939***	5.355***	4.345***	4.847***	4.659***	5.143***	3.703***
0.35	5.746***	4.069***	4.370***	5.889***	5.733***	6.144***	5.390***	4.506***	5.073***	4.751***	5.390***	4.124***
0.40	5.729***	4.083***	4.476***	5.824***	5.897***	6.470***	5.444***	4.557***	5.076***	5.324***	5.638***	4.147***
0.45	5.960***	4.096***	4.541***	6.010***	5.851***	6.625***	5.516***	4.551***	5.053***	5.481***	6.169***	3.890***
0.50	6.057***	4.141***	4.467***	5.854***	5.902***	6.674***	5.791***	4.857***	4.973***	5.512***	6.051***	3.790***
0.55	5.862***	4.088***	4.449***	5.735***	5.886***	6.611***	5.795***	4.916***	5.342***	5.392***	5.940***	3.727***
0.60	5.889***	4.100***	4.395***	5.667***	5.754***	6.641***	5.563***	4.871***	5.276***	5.233***	5.568***	3.676***
0.65	5.667***	3.932***	4.207***	5.629***	5.664***	6.348***	5.266***	4.637***	5.142***	5.277***	5.657***	3.544***
0.70	5.331***	3.796***	4.043***	5.289***	5.385***	6.116***	4.951***	4.317***	4.805***	4.919***	5.419***	3.542***
0.75	4.910***	3.441***	3.814***	4.911***	5.009***	5.738***	4.664***	3.992***	4.642***	4.841***	5.037***	3.396***
0.80	4.515***	3.274***	3.517***	4.377***	4.624***	5.237***	4.402***	3.587***	4.200***	4.390***	4.703***	3.178***
0.85	4.178***	2.784***	3.179***	4.078***	4.061***	4.617***	4.069***	3.270***	3.984***	4.085***	4.149***	2.742***
0.90	3.324***	2.233**	2.665***	3.299***	3.191***	3.903***	3.414***	2.669***	3.144***	3.093***	3.394***	2.454**
0.95	2.382**	1.551	1.931*	2.404**	2.220**	2.711***	2.246**	2.061**	1.980**	2.127**	2.450**	1.848*

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to squared commodity returns for a particular quantile.

Table 5. *k*th order causality-in-quantiles test results on squared commodity returns (volatility) due to SV.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	2.028**	1.434	2.267**	2.102**	1.549	2.143**	1.766*	2.504**	4.128***	1.728*	1.571	1.321	2.519**
0.10	2.613***	2.280**	2.786***	3.251***	1.952*	2.490**	2.237**	3.383***	5.707***	2.205**	2.732***	2.400**	3.764***
0.15	3.244***	2.653***	3.571***	3.744***	2.861***	3.435***	2.495**	4.061***	6.773***	2.549**	3.109***	2.475**	4.594***
0.20	3.372***	2.995***	4.262***	4.190***	3.537***	3.719***	2.665***	4.324***	7.428***	3.389***	3.437***	2.513**	4.973***
0.25	3.569***	3.027***	4.460***	4.590***	3.909***	4.399***	2.694***	4.711***	8.052***	3.914***	3.784***	2.934***	5.228***
0.30	3.607***	2.921***	4.851***	4.907***	3.982***	4.627***	3.169***	5.103***	8.524***	3.996***	3.852***	2.993***	5.378***
0.35	3.890***	3.106***	5.125***	5.702***	4.251***	4.688***	3.207***	5.722***	9.058***	4.037***	3.563***	2.835***	5.982***
0.40	3.999***	3.143***	5.198***	5.949***	4.267***	4.613***	3.582***	6.006***	9.316***	4.413***	4.039***	3.334***	5.819***
0.45	4.309***	3.586***	5.224***	5.269***	4.570***	4.718***	3.705***	5.945***	9.521***	4.599***	4.219***	3.187***	5.859***
0.50	4.353***	3.384***	5.156***	5.603***	4.659***	4.916***	3.593***	5.710***	9.609***	4.556***	4.044***	3.118***	6.005***
0.55	4.175***	3.130***	5.511***	5.317***	4.341***	4.698***	3.743***	5.792***	9.396***	4.730***	4.263***	2.843***	5.809***
0.60	4.084***	3.133***	6.092***	5.359***	4.119***	5.087***	3.447***	5.964***	9.125***	4.420***	4.300***	3.019***	5.705***
0.65	3.810***	3.185***	5.945***	5.186***	3.868***	4.924***	3.382***	5.869***	8.914***	4.317***	4.228***	2.958***	5.533***
0.70	3.820***	2.964***	5.770***	4.638***	3.756***	4.742***	3.389***	5.620***	8.634***	3.958***	4.137***	2.821***	5.400***
0.75	3.692***	2.574**	5.281***	4.055***	3.362***	4.295***	3.051***	5.209***	8.132***	4.043***	3.869***	2.780***	5.193***
0.80	3.317***	2.546**	4.987***	3.779***	2.992***	4.283***	2.741***	4.679***	7.399***	3.534***	3.746***	2.314**	4.835***
0.85	2.890***	2.156**	3.993***	3.411***	2.631***	3.405***	2.617***	4.018***	6.687***	2.848***	3.107***	1.959*	4.373***
0.90	2.329**	1.703*	2.934***	3.078***	1.959*	2.871***	2.287**	3.089***	5.539***	2.251**	2.662***	1.693*	3.801***
0.95	1.811*	1.06	1.942*	2.253**	1.423	1.956*	1.356	2.035**	4.163***	1.221	1.786*	1.065	2.372**

Table 5. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	1.911*	1.647*	2.095**	2.003**	2.580***	2.514**	1.817*	1.835*	1.943*	1.656*	1.708*	1.491
0.10	3.072***	2.318**	2.878***	2.672***	3.200***	3.549***	2.728***	2.446**	2.460**	2.514**	2.616***	2.388**
0.15	3.626***	2.443**	3.194***	3.553***	3.849***	4.552***	3.097***	2.994***	3.309***	2.744***	2.939***	3.154***
0.20	4.392***	2.828***	3.525***	4.702***	4.120***	5.496***	3.579***	3.275***	3.779***	3.007***	3.399***	3.394***
0.25	4.612***	3.129***	4.070***	4.560***	4.801***	5.603***	4.241***	3.638***	4.278***	3.075***	3.487***	3.353***
0.30	4.527***	3.904***	4.207***	4.672***	4.770***	5.988***	4.449***	4.046***	4.281***	3.485***	3.717***	3.660***
0.35	5.250***	4.094***	4.621***	4.796***	5.173***	6.248***	4.583***	4.136***	4.514***	3.689***	4.055***	3.627***
0.40	5.219***	4.278***	4.656***	5.132***	5.478***	6.427***	4.656***	4.197***	4.873***	3.755***	3.993***	3.697***
0.45	5.345***	4.135***	4.644***	5.561***	5.480***	6.508***	5.268***	4.283***	4.709***	3.986***	4.250***	3.392***
0.50	5.237***	4.294***	4.621***	5.489***	5.447***	6.474***	5.401***	4.152***	5.301***	4.224***	4.450***	3.557***
0.55	5.600***	4.214***	4.557***	5.257***	5.343***	6.664***	4.734***	4.275***	4.897***	4.067***	4.357***	3.636***
0.60	5.303***	4.234***	4.453***	5.048***	5.291***	6.356***	4.672***	3.923***	4.558***	4.285***	4.299***	3.750***
0.65	5.396***	4.080***	4.327***	4.921***	5.220***	6.328***	4.260***	3.751***	4.098***	4.277***	4.456***	3.481***
0.70	5.091***	3.885***	4.117***	4.672***	5.398***	5.910***	3.980***	3.724***	3.633***	4.477***	4.342***	3.284***
0.75	4.766***	3.294***	3.868***	4.348***	5.296***	5.552***	3.959***	3.401***	3.710***	3.660***	4.045***	3.008***
0.80	4.388***	2.989***	3.556***	4.092***	4.926***	4.811***	3.716***	3.122***	3.421***	3.621***	3.615***	3.066***
0.85	3.974***	2.491**	3.158***	3.462***	3.867***	4.565***	3.232***	2.888***	2.967***	3.010***	2.939***	2.739***
0.90	3.278***	1.946*	2.638***	2.728***	3.132***	3.692***	2.530**	2.282**	2.137**	2.461**	2.380**	2.204**
0.95	2.217**	1.297	1.906*	1.805*	2.133**	2.644***	1.767*	1.876*	1.604	1.809*	1.615	1.600

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to squared commodity returns for a particular quantile.

volatility, this predictive effect is relatively strong and covers nearly the entirety of the conditional distribution of the various commodities, with the strongest effects around the median for most commodities. This means that climate risks can predict historical regime-specific movements of commodity-market returns, but causality to volatility is not necessarily restricted by the underlying state of volatility.

5. Conclusion

The objective of our research is to use a *k*th-order nonparametric causality-in-quantiles test to analyze the causal effect of climate-related risks on returns and volatility of 25 important commodities, spanning the overall historical period of 1258 to 2021. The usage of the longest possible data available for the commodities ensures robust inference regarding the predictive effects of climate risks by avoiding concerns of sample-selection bias. At the same time, the methodology adopted is robust to nonlinearity and regime changes, which is likely to exist in the long data sample that we study, while determining causality for both returns and volatility over their corresponding conditional distributions. With quantiles capturing regimes of commodity returns and volatility, the test is inherently a time-varying one and is apt for capturing the entire historical evolution of these commodities. Based on changes in the global temperature anomaly (DT) and its SV, as metrics of rare-disaster risks emanating due to climate changes, we can draw the following conclusions: (i) Barring the case of predictability of gold and oil returns due to SV, linear Granger causality test fails to find any evidence of commodity-returns predictability emanating from the climate risks variables. (ii) In contrast, tests of nonlinearity and regime changes find overwhelming evidence of the linear framework being misspecified. (iii) Hence, relying on the robust *k*th order nonparametric causality-in-quantiles test, we find evidence of climate risks predicting both returns and volatility of all of the 25 commodities considered. (iv) The results from the causality-in-quantiles test also tend to suggest that, as far as returns are concerned, extreme quantiles remain nonpredictable due to climate risks, but DT and SV predict virtually the entire conditional distribution of volatility, though the effects are weaker at the tails. These four key findings are intuitive in the sense that when commodity markets are performing poorly or exceptionally well, market agents possibly herd (Júnior *et al.*, 2020) and do not require outside information due to climate risks to predict future returns. However, when the markets performing normally, commodity investors are likely to look for climate-risks-related information to improve or enhance returns on their portfolios. Furthermore, it is not surprising to see a stronger second-moment impact of DT and SV on commodity returns volatility, i.e., risk, due to both these variables measuring uncertainty associated with climate change-based disaster risks, especially given that rare disaster events reflect an aggregate jump risk, with the latter being an important component of volatility (Gupta *et al.*, 2019a,b).

In general, academically speaking, our results highlight the importance of accounting for nonlinearity when dealing with the nexus between historical commodity-market movements and climate risks, since inference based on linear models is likely to be erroneous. In this regard, what is also important is analyzing the entire conditional distributions of both returns and volatility. Moreover, our results can be used by policymakers to obtain information on the movements of the first- and second moments of commodity-price fluctuations due to changes in climate patterns, and in the process, to use this knowledge to form better forecasts of economic activity, given that commodity-price movements are known to lead business cycles, and then accordingly make appropriate policy choices. Moreover, the regime-specific predictability of returns and volatilities of commodities due to climate risks should be of vital importance to investors in terms of making portfolio decisions.

Overall, our results direct policymakers and investors to rely on a state-contingent nonparametric framework capturing the relationship between commodities and risks of climate change, rather than a linear model, before making their policy and investment decisions. Purely in an academic context, this model can be used to predict historical movements in returns and volatility of commodity markets. In this regard, as part of future research, it is interesting to extend our analysis to an out-of-sample forecasting exercise as in Bonaccolto *et al.* (2018), because in-sample predictability does not necessarily guarantee the same over out-of-sample periods. Naturally, though informative, our paper being restricted to in-sample predictability remains limited as it is unable to provide real-time forecasts. Another issue in this regard would be to account for possible spillover across the commodities while analyzing the impact of climate risks, but, this in turn, would require a vector autoregressive (VAR) framework and hence, a balanced sample period.

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Appendix A

Table A.1. Summary statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations	Start	End
Aluminum	−3.721	−2.353	51.604	−93.559	17.805	−0.715	7.39	151.906***	171	1851	2021
Banana	−0.086	0.465	36.467	−43.948	11.524	−0.025	4.764	15.697***	121	1901	2021
Beef	−0.016	−0.038	67.01	−52.162	11.845	0.554	9.254	623.544***	371	1651	2021
Coal	−0.1	−0.788	82.738	−44.149	13.372	1.139	8.842	607.770***	371	1651	2021
Cocoa	−1.005	0.238	104.019	−59.319	22.254	0.341	5.113	45.401***	221	1801	2021
Coffee	−1.025	−1.271	92.7	−67.654	19.611	0.609	6.803	207.334***	312	1710	2021
Copper	−0.496	−0.874	56.938	−68.355	17.142	−0.108	4.207	13.836***	221	1801	2021
Cotton	−0.522	0.38	166.643	−160.427	23.531	0.216	15.56	2309.747***	351	1671	2021
Gold	−0.296	−0.44	137.96	−41.58	11.591	2.153	30.461	24595.820***	764	1258	2021
Hide	−0.537	−0.899	62.046	−90.904	19.652	−0.539	6.46	120.940***	221	1801	2021
Iron	−0.835	−0.978	58.517	−47.856	14.705	0.224	5.037	43.324***	239	1783	2021
Jute	−0.427	1.849	66.056	−92.016	23.852	−0.582	4.546	18.878***	121	1901	2021
Lamb	−0.196	−0.627	74.089	−64.03	12.533	0.781	11.91	1264.998***	371	1651	2021
Lead	−0.292	−0.341	58.804	−52.765	13.517	−0.022	6.146	153.073***	371	1651	2021
Nickel	−1.049	−1.477	91.858	−63.02	19.585	0.415	6.277	86.177***	181	1841	2021
Oil	−1.221	−1.065	114.749	−296.924	34.666	−3.605	35.001	7263.471***	162	1860	2021
Rice	−1.093	−1.297	98.125	−103.938	19.846	0.043	8.036	353.106***	334	1688	2021
Silver	−0.489	−0.948	50.566	−65.188	13.187	0.358	7.364	272.191***	334	1688	2021
Sugar	−1.272	−0.591	103.091	−131.35	21.098	−0.142	12.537	1407.366***	371	1651	2021
Tea	−1.682	−3.008	58.724	−73.651	16.565	0.106	5.414	85.146***	348	1674	2021
Tin	0.28	−0.162	50.359	−78.443	17.324	−0.317	5.704	68.461***	213	1809	2021
Tobacco	0.109	−1.092	87.572	−47.074	15.656	0.761	6.879	202.568***	280	1742	2021
Wheat	−0.695	−0.697	62.106	−47.857	15.274	0.009	3.965	14.413***	371	1651	2021
Wool	−0.685	−0.894	78.023	−90.445	18.761	−0.076	6.005	139.948***	371	1651	2021

Table A.1. (*Continued*)

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations	Start	End
Zinc	−0.123	0.494	85.74	−68.212	20.786	0.495	6.599	97.517***	168	1854	2021
DT	0.001	−0.001	0.358	−0.317	0.078	0.087	4.405	63.816***	764	1258	2021
SV	0.005	0.004	0.014	0.002	0.004	1.334	3.006	226.461***	764	1258	2021
Garch	0.006	0.004	0.017	0.002	0.004	1.403	3.447	256.844***	764	1258	2021
COMB ENSO	0.571	1	1	0	0.495	−0.289	1.083	82.977***	497	1525	2021

Notes: Std. Dev. stands for standard deviation; The null hypotheses of the Jarque-Bera test correspond to the null of normality; *** indicates rejection of the null hypothesis at the 1% level of significance.

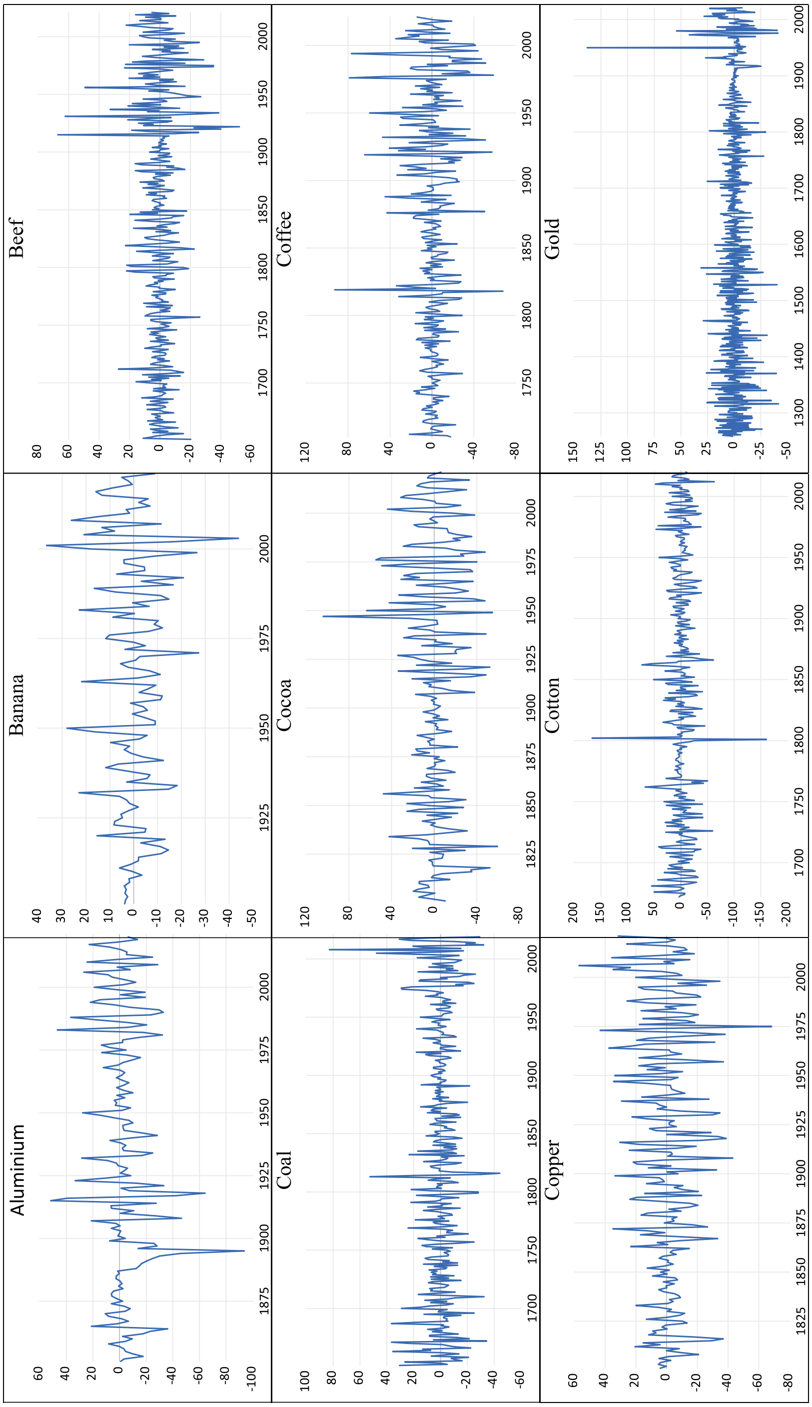

Figure A.1. Real commodity returns data plots.

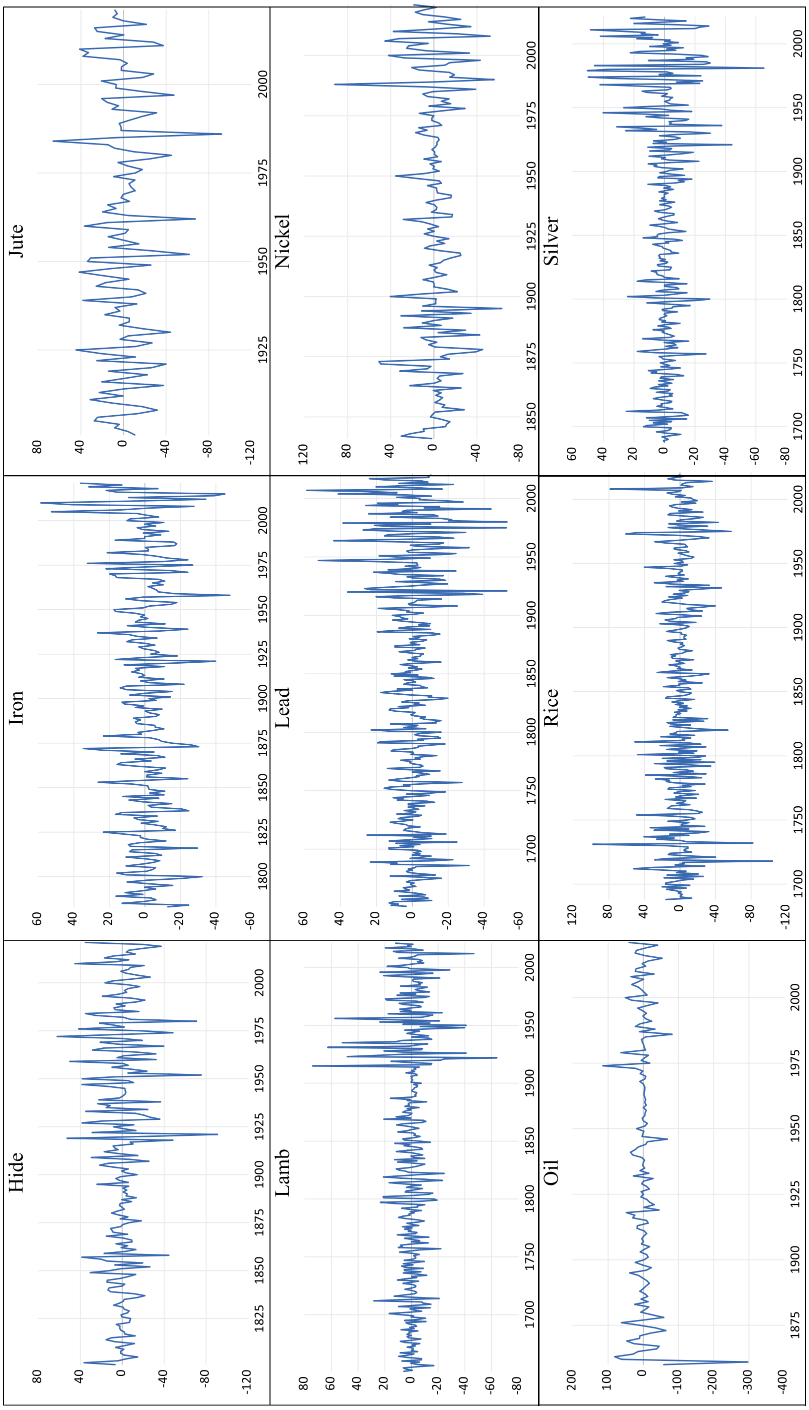

Figure A.1. (*Continued*)

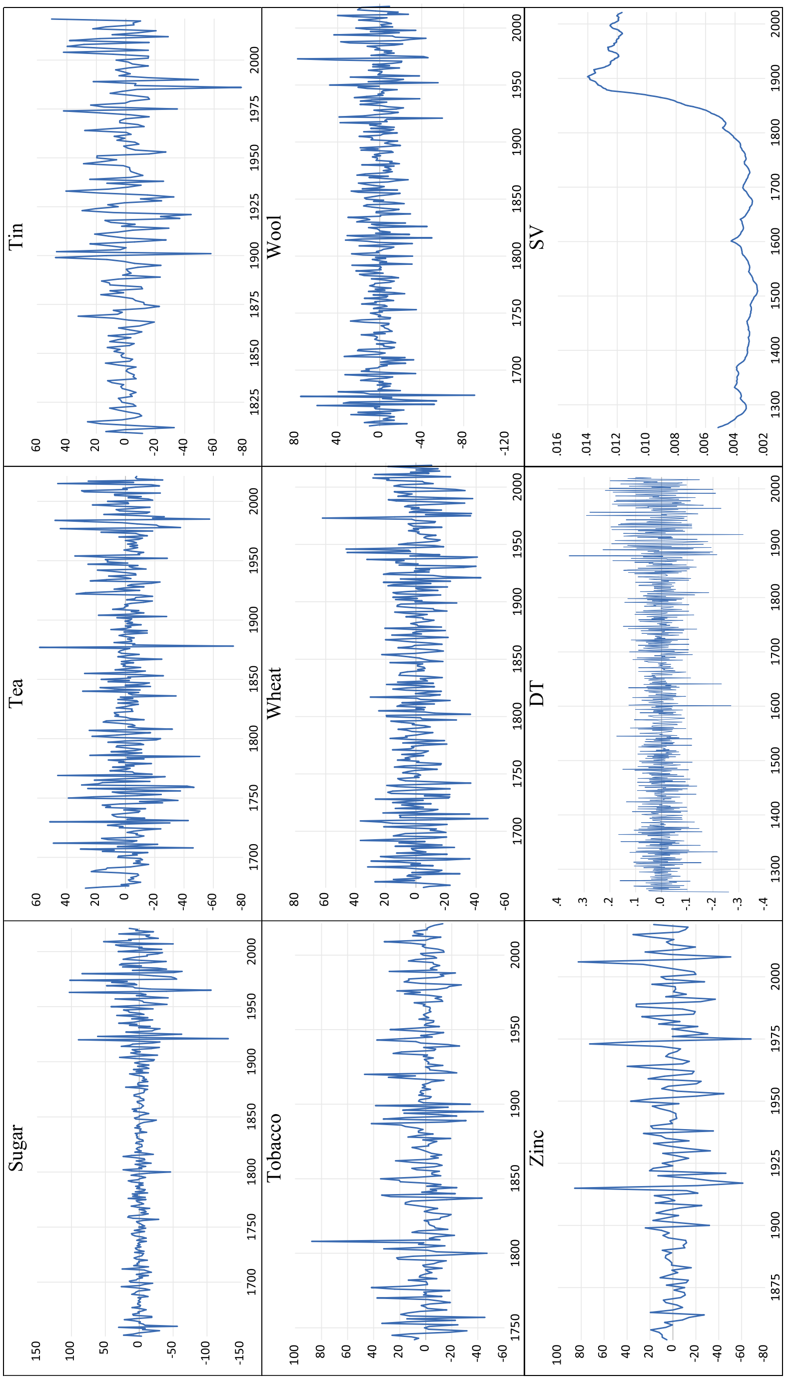

Figure A.1. (*Continued*)

Table A.2. Brock *et al.* (1996, BDS) test of nonlinearity.

Dependent variable	*m* Predictor	2	3	4	5	6
Aluminum	DT	3.255***	4.961***	5.588***	5.867***	5.719***
	SV	3.213***	4.535***	4.931***	5.134***	4.923***
Banana	DT	3.166***	3.528***	3.448***	3.307***	2.839***
	SV	1.772*	2.620***	2.868***	2.776***	2.473**
Beef	DT	5.733***	6.884***	8.172***	9.199***	10.109***
	SV	5.870***	7.088***	8.329***	9.313***	10.237***
Coal	DT	5.272***	6.672***	6.761***	7.225***	7.287***
	SV	6.247***	7.183***	7.139***	7.517***	7.585***
Cocoa	DT	2.762***	2.826***	3.397***	3.710***	3.936***
	SV	2.508**	2.305**	3.054***	3.399***	3.637***
Coffee	DT	4.697***	6.340***	7.315***	8.289***	9.258***
	SV	4.706***	6.156***	7.089***	8.118***	9.178***
Copper	DT	0.345	1.726*	2.051**	2.634***	2.502**
	SV	0.571	1.826*	2.450**	2.968***	2.767***
Cotton	DT	4.185***	4.993***	5.531***	5.928***	6.536***
	SV	3.905***	4.308***	5.069***	5.340***	5.989***
Gold	DT	8.101***	9.800***	11.284***	12.495***	13.748***
	SV	7.472***	9.377***	10.956***	12.212***	13.363***
Hide	DT	3.954***	5.576***	6.130***	7.032***	8.467***
	SV	2.795***	4.457***	5.125***	6.083***	7.329***
Iron	DT	3.707***	4.974***	4.198***	4.685***	5.045***
	SV	3.570***	4.881***	4.196***	4.634***	4.897***
Jute	DT	−0.548	0.403	0.474	0.401	0.266
	SV	−0.171	0.736	0.795	0.706	0.510
Lamb	DT	3.138***	4.795***	5.775***	6.790***	7.471***
	SV	3.614***	5.242***	6.379***	7.500***	8.197***
Lead	DT	6.205***	7.695***	8.504***	9.174***	9.670***
	SV	6.765***	8.112***	8.864***	9.488***	9.949***
Nickel	DT	1.839*	3.812***	4.509***	4.618***	4.962***
	SV	3.128***	4.699***	5.157***	5.343***	5.745***
Oil	DT	12.968***	11.698***	10.575***	9.713***	9.041***
	SV	0.966	1.221	1.736*	2.033**	2.621***
Rice	DT	3.000***	2.914***	3.704***	4.142***	4.345***
	SV	2.659***	2.422**	2.952***	3.272***	3.538***
Silver	DT	6.490***	9.422***	10.876***	12.097***	13.349***
	SV	6.604***	9.483***	11.110***	12.431***	13.679***
Sugar	DT	8.972***	10.950***	12.820***	14.440***	16.444***
	SV	8.654***	10.963***	12.881***	14.427***	16.400***
Tea	DT	6.386***	7.074***	7.156***	7.055***	6.867***
	SV	7.067***	7.400***	7.612***	7.667***	7.544***
Tin	DT	1.305	2.909***	3.926***	4.850***	5.728***
	SV	1.816*	3.366***	4.285***	4.949***	5.708***
Tobacco	DT	5.244***	5.305***	5.417***	5.817***	6.348***
	SV	5.270***	5.399***	5.496***	6.078***	6.616***
Wheat	DT	1.100	1.573	2.435**	3.255***	4.043***

Table A.2. (*Continued*)

Dependent variable	*m* Predictor	2	3	4	5	6
	SV	1.090	1.744*	2.384**	2.936***	3.636***
Wool	DT	4.961***	4.724***	5.387***	5.638***	5.583***
	SV	5.199***	4.777***	5.325***	5.472***	5.317***
Zinc	DT	2.657***	3.262***	3.644***	3.613***	3.127***
	SV	2.675***	3.270***	3.576***	3.463***	2.929***

Notes: Entries correspond to the z-statistic of the BDS test with the null of i.i.d. residuals, with the test applied to the residuals recovered from the commodity returns equation with SIC-based lags each of commodity returns and a particular climate risk factor; ***, **, and * indicate rejection of the null hypothesis at 1%, 5%, and 10% levels of significance.

Table A.3. Multiple breaks test.

		Dates	
Commodity	Predictor	*Udmax*	*Wdmax*
Aluminum	DT	1899	1899
	SV	1899	1879, 1908, 1934, 1983
Banana	DT		1932, 1952, 2004
	SV	1933, 1986, 2004	1922, 1951, 1971, 1988, 2005
Beef	DT	1791, 1846, 1921	1709, 1773, 1831, 1897, 1952
	SV		1709, 1768, 1830, 1889, 1944
Coal	DT		
	SV		
Cocoa	DT	1836, 1977	1836, 1905, 1937, 1980
	SV	1980	1836, 1876, 1914, 1946, 1979
Coffee	DT		1767, 1820, 1868, 1919, 1976
	SV	1930, 1976	1930, 1976
Copper	DT		
	SV		
Cotton	DT		1750, 1802, 1862, 1914, 1969
	SV		1750, 1802, 1857, 1911, 1969
Gold	DT		1388, 1590, 1704, 1818
	SV	1907	1907
Hide	DT		
	SV	1859, 1891, 1923, 1958, 1990	1859, 1891, 1923, 1958, 1990
Iron	DT		1820, 1859, 1894, 1933, 1968
	SV	1873, 1908, 1951, 1986	1837, 1873, 1908, 1951, 1986
Jute	DT	1938, 1955	1938, 1955
	SV		1952, 1983, 2002
Lamb	DT	1781, 1846, 1936	1712, 1768, 1823, 1881, 1936
	SV	1777, 1833, 1927	1712, 1777, 1833, 1927
Lead	DT		1739, 1804, 1859, 1921

Table A.3. (*Continued*)

Commodity	Predictor	Dates	
		Udmax	*Wdmax*
	SV		
Nickel	DT	1995	1995
	SV	1984	1984
Oil	DT		
	SV	1894, 1919, 1944, 1970, 1994	
Rice	DT		
	SV	1740, 1792, 1846, 1913, 1969	1740, 1792, 1846, 1913, 1969
Silver	DT		
	SV		
Sugar	DT		
	SV		
Tea	DT		
	SV		1749, 1803, 1855, 1906, 1957
Tin	DT		
	SV	1857, 1889, 1922, 1960, 1991	1857, 1889, 1922, 1960, 1991
Tobacco	DT	1878, 1919	1878, 1919
	SV	1878, 1921	1787, 1839, 1880, 1921, 1964
Wheat	DT		1734, 1797, 1901, 1960
	SV		
Wool	DT		1713, 1769, 1831, 1909, 1965
	SV	1713	1713, 1769, 1831, 1893, 1952
Zinc	DT		1894, 1918, 1945, 1974, 1998
	SV		1894, 1918, 1951, 1976

Notes: The test is applied to the linear regression of commodity returns as the dependent variable and a climate risks measure (DT, SV) as the independent variable.

Table A.4. *k*th order causality-in-quantiles test results on commodity returns due to GARCH.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	1.306	0.628	1.298	1.015	1.164	1.125	1.000	0.959	1.118	1.013	0.826	0.605	0.979
0.10	1.871*	0.971	1.384	1.188	2.139**	1.209	1.687*	1.44	1.053	1.521	1.192	0.556	1.013
0.15	2.082**	1.244	0.977	1.616	2.261**	1.876*	1.979**	1.996**	1.247	1.918*	1.662*	0.751	1.302
0.20	2.044**	1.296	0.975	1.882*	3.081***	2.135**	2.400**	2.151**	1.352	1.960**	1.708*	0.890	1.113
0.25	1.930*	1.436	1.221	1.770*	3.161***	1.890*	2.309**	2.334**	1.701*	2.308**	2.590***	1.103	1.143
0.30	1.986**	1.449	1.172	2.152**	3.846***	1.784*	2.357**	2.088**	1.593	2.377**	2.475**	1.217	0.995
0.35	2.050**	1.243	1.169	2.805***	4.187***	1.755*	2.117**	2.444**	1.573	2.478**	2.217**	1.190	1.180
0.40	1.988**	1.558	1.132	2.070**	3.315***	1.725*	2.540**	2.736***	1.903*	1.855*	1.725*	1.261	1.383
0.45	2.206**	1.763*	1.500	1.823*	2.860***	1.865*	2.118**	2.904***	1.968**	1.851*	1.647*	0.958	1.685*
0.50	2.215**	1.767*	1.493	2.027**	2.176**	1.699*	1.978**	2.489**	2.318**	1.688*	2.237**	0.873	1.723*
0.55	2.205**	2.208**	1.736*	1.443	2.381**	1.903*	1.921*	2.340**	2.653***	1.507	2.284**	0.768	1.960*
0.60	2.263**	2.135**	1.559	1.220	2.199**	2.123**	1.969**	2.041**	2.695***	2.137**	2.076**	0.787	2.119**
0.65	1.975**	1.566	1.343	1.597	2.205**	2.429**	1.829*	2.002**	2.854***	2.383**	2.178**	0.727	1.962**
0.70	1.956*	1.295	1.192	1.537	2.108**	1.691*	1.970**	1.894*	2.227**	2.658***	1.895*	0.783	1.474
0.75	2.075**	1.410	1.332	2.126**	2.062**	2.238**	2.323**	1.795*	1.979**	2.614***	2.044**	0.903	1.302
0.80	1.724*	1.224	2.001**	2.038**	1.533	2.513**	2.071**	1.795*	1.772*	1.781*	2.243**	0.855	1.354
0.85	1.655*	1.570	2.570**	1.811*	1.374	2.638***	1.806*	1.608	1.673*	1.736*	2.171**	0.647	1.157
0.90	1.451	1.391	1.786*	1.435	1.006	2.694***	1.810*	1.508	1.684*	1.292	1.728*	0.651	1.433
0.95	0.994	0.549	1.229	1.176	0.733	1.24	0.889	0.774	1.201	0.68	1.119	0.478	1.231

Table A.4. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	1.132	0.749	1.236	0.736	1.668*	1.819*	0.828	1.658*	0.931	0.713	0.653	1.118
0.10	1.774*	0.858	1.328	1.075	1.918*	3.194***	1.289	2.640***	1.463	0.965	0.883	1.747*
0.15	1.939*	1.728*	1.586	1.569	1.879*	2.557**	1.227	3.182***	1.445	1.067	1.346	1.638
0.20	1.994**	1.851*	1.834*	1.853*	1.831*	2.866***	1.442	3.444***	1.680*	1.225	1.798*	2.005**
0.25	1.888*	2.107**	2.201**	2.106**	1.637	2.311**	1.495	4.190***	2.310**	1.294	1.861*	2.148**
0.30	1.606	2.110**	2.311**	2.032**	1.552	1.859*	1.874*	4.038***	2.238**	1.586	1.640	2.568**
0.35	1.506	2.849***	2.599***	1.947*	1.481	1.671*	1.873*	4.311***	2.355**	1.172	1.702*	2.818***
0.40	1.602	2.774***	2.462**	2.270**	1.554	1.632	1.599	4.271***	1.851*	0.949	1.808*	3.055***
0.45	1.655*	2.190**	2.879***	2.354**	1.503	1.739*	2.047**	4.226***	2.190**	0.804	1.372	1.904*
0.50	1.203	2.439**	2.841***	2.292**	1.339	2.037**	2.139**	4.434***	2.421**	0.845	1.478	1.857*
0.55	1.513	2.377**	2.643***	2.355**	1.338	1.590	2.305**	4.362***	2.547**	1.148	1.739*	1.643
0.60	1.625	2.670***	2.915***	2.669***	1.217	1.929*	2.437**	4.439***	2.943***	0.930	1.540	1.071
0.65	2.070**	2.301**	3.186***	2.977***	1.245	2.189**	2.190**	4.287***	3.028***	0.994	1.827*	1.172
0.70	1.990**	2.225**	3.312***	2.997***	1.465	3.644***	2.176**	4.041***	2.869***	0.805	2.053**	1.223
0.75	2.439**	2.216**	3.148***	2.978***	1.965**	3.928***	2.049**	3.740***	2.870***	0.723	2.413**	1.036
0.80	2.585***	2.389**	2.720***	2.196**	2.351**	3.462***	1.675*	3.464***	2.284**	0.807	2.042**	1.076
0.85	2.673***	2.285**	2.259**	1.705*	2.369**	3.119***	2.122**	3.051***	2.029**	0.584	1.399	1.001
0.90	3.126***	1.573	1.578	1.243	1.814*	2.278**	1.622	2.440**	1.674*	0.584	1.262	1.083
0.95	1.222	0.748	1.061	0.569	1.352	1.658*	1.113	1.748*	0.986	0.465	0.976	0.637

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to commodity returns for a particular quantile.

Table A.5. *k*th order causality-in-quantiles test results on commodity returns due to COMB ENSO.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	0.822	0.584	0.982	0.787	0.693	0.716	0.427	0.654	0.944	0.625	0.507	0.323	0.700
0.10	1.111	1.424	1.594	0.736	1.165	1.107	0.843	1.157	1.911*	1.102	0.534	0.317	0.700
0.15	1.558	1.692*	1.702*	1.029	1.678*	1.313	0.934	1.283	1.784*	1.212	0.880	0.332	0.864
0.20	1.462	1.486	1.666*	1.281	2.103**	1.252	1.373	1.217	1.882*	0.869	1.060	0.461	1.116
0.25	1.528	1.162	0.837	1.416	2.272**	0.912	1.183	1.403	2.647***	1.371	1.404	0.590	0.984
0.30	1.565	0.922	0.964	1.414	2.556**	0.784	1.346	1.235	2.881***	1.065	1.850*	0.614	1.273
0.35	1.722*	0.924	0.493	1.456	2.727***	0.957	1.643	1.101	2.720***	0.847	1.615	0.582	1.596
0.40	1.316	1.340	0.783	1.220	1.994**	1.141	1.144	1.094	2.048**	1.011	1.102	0.982	1.092
0.45	1.306	1.686*	1.079	1.391	1.421	1.717*	0.712	0.863	2.294**	0.589	0.758	0.856	1.276
0.50	1.354	2.238**	1.121	1.349	0.722	1.589	0.335	0.908	1.958*	0.747	0.641	0.815	1.750*
0.55	1.606	2.833***	1.383	1.361	0.704	1.977**	0.306	1.189	2.074**	0.723	0.769	0.645	1.446
0.60	1.851*	3.015***	1.026	1.039	0.840	1.644	0.269	1.217	2.425**	0.682	0.658	0.719	1.287
0.65	1.388	1.982**	0.567	1.819*	0.831	2.004**	0.442	1.138	3.069***	0.725	0.594	0.715	1.596
0.70	1.408	1.716*	0.489	2.020**	0.748	1.197	0.356	1.405	2.480**	0.930	0.774	0.697	1.263
0.75	1.305	1.765*	0.506	2.320**	0.872	1.248	0.516	1.219	2.233**	1.456	0.847	0.932	1.276
0.80	0.937	1.510	0.801	1.904*	0.554	1.145	0.207	1.076	1.744*	1.242	0.971	0.527	1.300
0.85	1.045	1.068	0.749	1.648*	0.515	0.848	0.213	1.240	1.848*	0.978	1.344	0.181	0.799
0.90	0.774	0.613	0.586	0.766	0.456	0.880	0.164	1.289	1.795*	0.670	0.894	0.211	0.654
0.95	0.711	0.196	0.458	0.884	0.305	0.643	0.175	0.498	1.023	0.279	0.601	0.189	0.707

Table A.5. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	0.595	0.390	0.417	0.960	1.383	1.610	0.774	0.777	0.693	0.551	0.459	0.638
0.10	0.878	0.660	0.662	0.889	1.992**	2.827***	0.822	0.963	1.044	0.679	0.817	0.987
0.15	1.165	0.979	0.619	1.219	1.325	2.258**	1.005	1.322	0.857	0.811	1.236	1.097
0.20	1.227	0.954	0.485	1.360	1.068	2.014**	0.715	1.183	1.031	0.639	1.617	1.370
0.25	1.272	0.875	1.002	1.400	1.273	1.623	0.690	1.072	1.278	0.774	1.623	1.356
0.30	1.189	0.783	0.978	1.360	1.491	1.315	0.788	1.022	1.346	1.026	1.497	1.571
0.35	1.697*	1.232	1.004	1.093	1.668*	1.223	0.951	1.415	1.167	0.915	1.613	1.314
0.40	1.347	1.062	1.097	1.014	1.932*	1.270	1.146	1.678*	0.758	0.879	2.012**	1.805*
0.45	1.627	1.515	1.115	0.750	1.556	1.302	0.962	1.810*	0.766	0.814	1.551	1.243
0.50	1.285	1.142	1.444	0.811	1.693*	1.594	1.394	2.021**	1.026	0.887	1.418	1.013
0.55	1.268	1.038	1.319	0.654	1.704*	1.168	1.764*	1.911*	1.366	0.870	1.157	0.932
0.60	1.434	1.162	1.710*	0.801	1.902*	1.163	1.449	2.409**	1.920*	0.837	1.237	0.813
0.65	1.594	1.384	2.089**	0.930	1.942*	1.133	1.655*	2.311**	2.858***	0.783	1.277	1.084
0.70	1.544	1.307	2.278**	0.851	1.742*	1.256	1.770*	2.135**	2.453**	0.688	1.459	0.693
0.75	2.203**	1.877*	2.697***	1.029	1.493	1.076	1.762*	2.177**	2.771***	0.696	1.222	0.571
0.80	2.394**	1.909*	2.184**	0.939	1.444	1.258	1.767*	2.111**	1.964**	0.546	1.175	0.438
0.85	2.546**	2.068**	1.658*	0.616	0.946	1.138	1.884*	1.811*	1.775*	0.566	0.551	0.490
0.90	2.565**	1.906*	1.119	0.851	0.969	0.757	1.447	1.480	1.333	0.380	0.687	0.459
0.95	0.882	0.673	0.898	0.665	0.726	0.533	0.719	0.947	0.634	0.284	0.623	0.237

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to commodity returns for a particular quantile.

Table A.6. *k*th order causality-in-quantiles test results on squared commodity returns (volatility) due to GARCH.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	1.908*	1.551	2.429**	2.315**	2.007**	1.898*	1.742*	2.502**	4.193***	1.993**	1.806*	1.478	2.644***
0.10	2.622***	1.963**	3.321***	3.252***	2.419**	2.652***	2.305**	3.440***	5.905***	2.580***	2.504**	1.835*	3.410***
0.15	3.012***	2.240**	3.614***	3.977***	3.246***	2.970***	2.934***	4.111***	6.907***	3.221***	3.015***	2.337**	4.017***
0.20	3.617***	2.639***	4.064***	4.664***	3.687***	3.548***	3.232***	4.200***	7.727***	4.241***	3.403***	2.367**	4.511***
0.25	3.993***	2.912***	4.445***	4.967***	3.685***	4.002***	3.660***	4.753***	8.397***	4.504***	3.724***	2.528**	4.926***
0.30	3.938***	3.059***	5.102***	5.405***	4.082***	4.339***	3.997***	4.928***	8.900***	4.310***	4.136***	2.593***	5.299***
0.35	4.002***	3.345***	5.323***	5.788***	4.365***	4.805***	3.952***	5.168***	9.322***	4.284***	4.270***	2.455**	5.787***
0.40	3.998***	3.448***	5.254***	5.848***	4.208***	4.817***	4.392***	5.366***	9.522***	4.892***	4.306***	2.904***	6.033***
0.45	4.095***	3.328***	5.238***	5.715***	4.406***	5.254***	4.451***	5.326***	9.749***	5.006***	4.425***	3.232***	6.092***
0.50	4.069***	3.583***	5.207***	5.855***	4.494***	5.259***	5.210***	5.412***	9.714***	5.202***	4.234***	3.124***	5.981***
0.55	4.184***	3.689***	5.581***	5.716***	4.384***	5.393***	5.082***	5.292***	9.570***	5.262***	4.555***	3.137***	5.856***
0.60	4.122***	3.482***	5.252***	5.332***	4.293***	5.354***	4.552***	5.224***	9.436***	4.830***	4.174***	2.880***	5.796***
0.65	3.822***	3.354***	5.309***	5.345***	4.191***	5.140***	4.397***	5.205***	9.168***	4.546***	4.140***	2.686***	5.631***
0.70	3.787***	3.211***	4.876***	5.336***	4.034***	4.765***	4.216***	4.993***	8.806***	4.091***	4.125***	2.770***	5.692***
0.75	3.607***	2.958***	4.734***	5.072***	3.641***	4.453***	3.957***	4.716***	8.248***	4.159***	3.678***	2.743***	5.203***
0.80	3.398***	2.500**	4.439***	4.772***	3.194***	3.958***	3.659***	4.311***	7.457***	3.779***	3.210***	2.390**	4.676***
0.85	2.996***	2.143**	3.855***	4.019***	3.129***	3.136***	3.627***	3.743***	6.646***	3.285***	2.915***	2.166**	4.041***
0.90	2.611***	1.781*	2.968***	3.675***	2.321**	2.859***	2.700***	3.096***	5.520***	2.568**	2.500**	1.659*	3.501***
0.95	2.035**	1.187	1.978**	2.673***	1.594	1.871*	1.725*	2.214**	4.069***	1.693*	1.515	1.028	2.350**

Table A.6. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	2.109**	1.917*	2.149**	2.064**	2.043**	2.614***	1.966**	1.930*	2.035**	1.664*	2.048**	1.703*
0.10	2.642***	2.584***	2.924***	2.958***	2.585***	3.440***	2.666***	2.528**	3.102***	2.232**	3.015***	2.237**
0.15	3.257***	2.919***	3.221***	3.916***	3.601***	3.931***	3.226***	3.160***	3.689***	2.683***	4.163***	2.760***
0.20	3.584***	3.586***	3.578***	4.222***	3.656***	4.723***	3.590***	3.380***	4.091***	3.381***	4.214***	3.077***
0.25	3.819***	3.788***	3.895***	4.564***	4.302***	4.963***	4.040***	4.144***	4.904***	3.540***	4.454***	3.349***
0.30	4.258***	3.826***	4.092***	4.674***	4.689***	5.126***	4.193***	4.646***	5.134***	3.722***	4.474***	3.403***
0.35	4.699***	4.060***	4.237***	5.002***	4.807***	5.092***	4.403***	4.814***	5.229***	4.317***	4.596***	3.784***
0.40	4.797***	3.974***	4.334***	5.222***	4.767***	5.587***	4.470***	5.185***	5.378***	4.336***	4.969***	3.763***
0.45	5.037***	4.130***	4.341***	5.239***	5.104***	5.813***	4.679***	5.095***	5.447***	4.158***	5.149*1**	4.244***
0.50	5.067***	4.049***	4.347***	5.534***	4.893***	6.048***	4.801***	5.050***	5.388***	4.279***	5.049***	3.961***
0.55	4.770***	4.044***	4.334***	5.198***	4.890***	6.091***	4.638***	5.139***	5.354***	4.269***	5.326***	3.919***
0.60	4.766***	4.170***	4.265***	5.111***	4.743***	6.146***	4.575***	5.196***	5.018***	4.255***	5.095***	3.695***
0.65	4.589***	3.951***	4.205***	5.151***	4.765***	5.722***	4.265***	4.988***	4.697***	3.859***	4.989***	3.601***
0.70	4.741***	3.732***	4.019***	4.948***	5.110***	5.695***	4.378***	4.409***	4.213***	3.737***	4.889***	3.788***
0.75	4.574***	3.623***	3.813***	4.586***	4.728***	5.351***	4.013***	4.011***	4.155***	3.345***	4.642***	3.380***
0.80	4.133***	3.352***	3.539***	4.190***	4.252***	4.812***	3.953***	3.873***	3.576***	3.076***	4.153***	3.174***
0.85	3.737***	2.921***	3.169***	3.571***	3.704***	4.440***	3.695***	3.413***	3.355***	3.075***	3.289***	2.874***
0.90	2.984***	2.342**	2.657***	2.946***	2.948***	3.657***	2.517**	2.663***	2.815***	2.329**	2.747***	2.555**
0.95	1.884*	1.595	1.933*	2.122**	1.800*	2.499**	1.854*	2.017**	2.037**	1.518	1.857*	1.772*

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to squared commodity returns for a particular quantile.

Table A.7. *k*th order causality-in-quantiles test results on squared commodity returns (volatility) due to COMB ENSO.

Quantile	Aluminum	Banana	Beef	Coal	Cocoa	Coffee	Copper	Cotton	Gold	Hide	Iron	Jute	Lamb
0.05	0.676	0.603	1.417	0.732	0.410	0.231	0.764	1.045	0.803	0.685	0.542	0.640	0.812
0.10	0.768	1.158	1.096	0.855	0.829	0.606	1.006	1.068	1.002	0.440	0.857	0.573	0.990
0.15	0.667	1.114	1.095	0.676	1.295	0.927	1.279	1.295	1.310	0.512	1.125	0.682	1.126
0.20	0.534	1.783*	1.839*	0.769	1.866*	1.350	1.777*	1.009	1.426	1.205	0.759	0.686	1.295
0.25	0.799	1.388	1.395	0.770	2.497**	1.956*	1.830*	1.087	1.528	1.862*	1.126	1.381	1.288
0.30	1.571	0.861	1.087	1.090	2.613***	1.962**	2.447**	1.039	2.279**	1.726*	1.288	1.603	1.177
0.35	2.146**	0.830	0.914	2.300**	2.882***	1.829*	1.993**	1.154	2.515**	1.748*	1.366	1.315	1.685*
0.40	1.685*	1.062	0.823	2.457**	2.846***	1.616	1.940*	1.761*	3.482***	2.151**	0.922	1.575	1.636
0.45	1.689*	1.419	1.172	1.987**	2.636***	1.269	1.733*	1.351	3.920***	2.516**	0.957	1.295	1.902*
0.50	1.468	1.632	1.176	1.445	3.606***	1.642	2.054**	1.476	3.781***	3.045***	0.982	1.075	1.628
0.55	1.294	1.727*	0.974	1.669*	2.498**	0.953	2.074**	1.374	3.488***	3.061***	0.842	1.229	1.843*
0.60	1.189	1.882*	1.124	1.524	2.288**	1.148	1.860*	1.020	3.152***	2.472**	0.874	0.994	1.686*
0.65	0.939	1.615	1.370	1.427	2.219**	1.023	1.376	1.340	2.780***	1.572	0.634	0.984	1.759*
0.70	1.134	1.507	1.172	1.040	2.266**	1.164	1.703*	1.100	2.470**	1.443	0.864	1.236	1.310
0.75	1.199	1.324	1.070	0.943	1.783*	0.768	1.055	1.033	2.301**	2.325**	0.785	1.015	1.184
0.80	1.032	1.031	1.466	0.684	1.308	0.672	1.145	1.250	2.227**	1.938*	0.815	0.852	1.014
0.85	0.852	0.737	1.411	0.747	1.365	0.696	1.071	0.990	2.229**	1.351	0.622	0.519	1.157
0.90	0.713	0.462	0.785	1.460	0.644	0.395	0.556	0.857	1.892*	1.032	0.524	0.662	1.385
0.95	0.250	0.376	0.410	0.777	0.461	0.475	0.399	0.725	1.134	0.426	0.482	0.300	0.834

Table A.7. (*Continued*)

Quantile	Lead	Nickel	Oil	Rice	Silver	Sugar	Tea	Tin	Tobacco	Wheat	Wool	Zinc
0.05	0.715	0.476	0.726	0.677	0.658	0.627	0.525	0.435	0.978	0.405	0.484	0.588
0.10	1.407	0.588	0.878	0.533	0.623	0.642	0.697	0.446	1.086	0.611	0.754	0.625
0.15	1.387	1.121	1.229	0.998	0.850	0.640	0.637	0.809	0.968	0.978	1.004	1.358
0.20	1.704*	1.102	1.579	1.530	0.697	0.767	0.623	1.262	1.554	0.873	1.365	1.253
0.25	1.995**	1.276	1.962**	1.282	0.926	0.667	1.040	1.642	1.603	1.030	1.367	0.855
0.30	2.172**	1.535	1.895*	1.427	1.075	0.889	1.265	1.421	2.362**	1.313	1.153	1.111
0.35	2.043**	1.275	1.614	1.806*	1.259	1.135	1.492	1.596	2.129**	1.275	1.547	0.907
0.40	1.998**	1.309	1.266	1.529	1.134	1.236	1.314	1.506	2.497**	1.244	1.673*	0.844
0.45	2.079**	1.304	1.283	1.422	1.240	1.324	1.379	1.651*	2.667***	1.170	1.740*	1.027
0.50	2.240**	1.343	1.370	1.884*	1.018	1.321	1.482	2.022**	2.674***	1.514	1.899*	1.416
0.55	2.260**	1.493	1.408	2.016**	0.791	1.837*	1.228	1.827*	2.125**	1.511	1.807*	1.621
0.60	2.040**	1.311	1.282	2.747***	0.639	1.893*	1.232	2.237**	2.297**	1.299	1.680*	2.037**
0.65	2.000**	1.156	1.675*	1.941*	0.654	1.939*	1.173	2.486**	1.815*	1.602	1.945*	1.435
0.70	1.885*	1.258	2.289**	1.998**	0.726	1.411	1.143	2.227**	1.681*	1.817*	1.734*	1.883*
0.75	1.670*	1.038	1.638	1.537	0.729	1.358	0.967	1.881*	1.915*	1.218	1.227	1.585
0.80	1.528	0.813	1.483	1.513	1.118	1.201	1.172	2.054**	1.414	1.207	1.562	1.590
0.85	1.616	0.634	1.684*	1.086	1.152	1.120	0.958	1.946*	1.280	0.888	1.076	1.571
0.90	1.267	0.512	1.161	0.742	1.272	0.994	0.691	1.191	1.008	1.009	0.672	1.237
0.95	0.579	0.297	0.658	0.300	0.936	0.465	0.690	1.039	0.656	0.777	0.643	0.939

Notes: ***, **, and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5%, and 10% levels of significance (i.e., critical values of 2.575, 1.96, and 1.645) respectively, from a particular metric of climate risks to squared commodity returns for a particular quantile.

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