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CLIMATE RISK AND THE PREDICTABILITY OF JUMPS IN GREEN ASSETS

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Abstract

This paper shows that climate risk can help predict the size and direction of intraday jumps in green assets, both in and out-of-sample. Using tick data to capture the size and intensity of intraday jumps, we find that news that relate to transition climate risk including international summits and climate policy, particularly those that could be interpreted as bad news for brown industries, are the most dominant predictors of jumps in green assets compared to proxies of physical climate risks. Our findings provide a novel perspective to the role of climate risk as a driver of idiosyncratic tail risk and jump innovations in green assets and imply that pricing models that incorporate jump risk as a risk factor can be improved by exploiting the predictive power of climate risk over jump dynamics.

Keywords: Climate risk, stock market jumps, green investments, intraday returns

1. Introduction

Modeling jumps in stock prices has significant implications for the pricing and hedging in financial markets. Jumps refer to sudden and infrequent movements of large magnitude in the path of stock prices and the literature provides ample evidence that systematic jump risk accounts for a large percentage of the total equity risk premium, establishing a link between jump risk and idiosyncratic tail risk that is undiversifiable (Begin et al., 2020), while other works show that jump measures obtained from high frequency data can improve stock volatility forecasts (Bu et al., 2023). Considering investors should be rewarded for bearing systematic risk and the evidence that jumps serve as a systematic risk factor in expected stock returns (Dunham and Friesen, 2007), predictability of jumps becomes an important consideration for not only asset pricing, but also in portfolio allocation strategies. The main contribution of this study is to extend the study of jumps to the emerging literature on climate finance and examine the predictive role of climate risk on jumps in green assets.

A growing number of recent works on climate finance establish a link between climate risk and the cross-section of equity returns (Bolton and Kacperczyk, 2021; Faccini et al., 2023), while others examine green investments in the context of hedging against climate risks (Cepni et al., 2022). None of these studies, however, has examined the role of climate risk in the context of jump risk although a growing literature highlights climate policy uncertainty as a driver of price dynamics in green equities (Bouri et al., 2022). While stock price jumps can be associated with firm-specific events, unexpected market news or large arbitrage activities (Kong et al., 2021), the literature provides ample evidence that these discontinuous fluctuations in prices can have serious implications for pricing and asset allocation, which is an important consideration for the viability of sustainable investments. Looking ahead, our analysis shows that both the direction and size of price jumps in green markets can indeed be predicted via measures of climate risk, both in- and out-of-sample. We find that news captured by transition climate risk proxies including international summits and climate policy, particularly those that could be interpreted as bad news for brown industries, are the most dominant predictors of jumps in green assets compared to proxies of physical climate risks, in line with the evidence that the risk of government interventions, rather than the direct risks from climate change, serves as a more dominant driver of expected returns in equities. While international summits provide greater predictive contribution for positive jumps, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies. Considering that a significant portion of idiosyncratic risk in stocks can be attributed to jump risk (Begin et al., 2020), our findings suggest that measures of climate risk can help improve pricing models in green investments via its interaction with idiosyncratic volatility, thus opening a new line of explanation to the risk-return tradeoffs in green assets.

The remainder of the paper is organised as follows. Section 2 outlines the data and methodology. Section 3 presents the empirical results and Section 4 concludes with a discussion of the implications of our findings.

2. Data and Methodology

2.1 Data

We utilise tick data, obtained from the Thomson Reuters Tick History (TRTH) database, for the Invesco Global Clean Energy ETF that is comprised of companies engaged in cleaner energy and conservation globally. Also utilised by other works including Bouri et al. (2022) as a proxy for green technology stocks, this fund captures price movements in stocks that are engaged in the advancement of cleaner energy and conservation. Formed to replicate the performance of the WilderHill New Energy Global Innovation Index, the fund’s holdings include leaders in renewable energy technologies from a diverse set of industries including industrials, energy, information technology, utilities, and consumer discretionary. The data cleaning process involves consolidating duplicate quotes and transactions by replacing them with a single entry using the mean bid price, ask price or transaction price and cumulated trading volumes. Negative bid-ask spread entries are removed.

To assess climate-related risks, we use the climate indices developed by Faccini et al. (2023) via textual and narrative analysis of Reuters climate-change news. The authors compile a corpus of more than 13 million articles published in Reuters over the period Jan. 2000 to Dec. 2018. After an initial filtering based on the language, multiple entries and subsequent corrections in the articles, the authors end up with a sample of about seven million articles covering a diverse set of topics that include sports, technology, politics, finance, among others. Since the goal is to assess the coverage of climate related news in these articles, they discard irrelevant ones and keep only those in which the bigrams “climate change” or “global warming” occur at least once, yielding a final sample of roughly 34,000 articles. Since this final sample covers a rather heterogeneous set of articles related to climate change, the authors group the news into specific climate subcategories via the Latent Dirichlet Allocation method proposed by Blei et al. (2003). In this procedure, the collection of articles in the final sample is scanned based on a vocabulary of over 6,000 unique words to (i) decompose the entire textual corpus into topics identified by the machine learning algorithm that dissects textual heterogeneity into topics; and (ii) express each article as a probability weighted average of topics where each topic share reflects the intensity (frequency) by which a topic appears in that article. Once the machine learning algorithm delivers the topics, the authors then label them based on the words that appear most frequently. In the case of Faccini et al. (2023), the LDA model classifies the unique words into 25 different topics and by applying several criteria, the authors classify the topics into four general headings, namely natural disasters, global warming, U.S. climate policy (actions and debate), and international summits. Summing the topic shares across all the articles published in a given day, the authors then generate a measure of the intensity of news coverage for a given topic in a given day.

Following the argument by Engle et al. (2020) that the disclosure of news reveals risks for firms and investors, Faccini et al. (2023) interpret the daily time series of media news coverage of each topic as a measure of climate risk associated with the occurrence of natural disasters, global warming, U.S. climate policy (actions and debate), and international summits. In their setting, an increase in news coverage is interpreted as either an increase in the number of articles published or an increase in media attention to a particular climate topic. The authors argue that news about natural disasters and global warming typically signal adverse effects on the economy as such news raise media attention whenever it is a source of concern (Engle et al., 2020). Similarly, international summits also signal adverse effects on the economy as these meetings are typically associated with discussions on a global tax on pollutants, which is bad news for firm profitability. Climate policy, however, is relatively harder to interpret as one might argue that increased news coverage of the U.S. political debate on climate policy may reflect good or bad news for the economy depending on which party, Democrats or Republicans, holds the power. Nevertheless, their analysis shows that these climate risk proxies do not confound the effects associated with other sources of uncertainty like economic policy uncertainty or other political risks and are interpreted as risk factors based on their direct effects on stakeholders. Based on the availability of the climate risk series and intraday ETF data, the sample period spans from June 2007 to November 2019.

Intraday price jumps are identified following Lee and Mykland (2008). The observed log mid-prices *p* are generated in a continuous time Brownian semi-martingale process with finite activity jumps:

$$dp(s) = \mu(s)ds + \sigma(s)dW(s) + k(s)dq(s) \tag{1}$$

where $\mu(s)$ is the drift term with a continuous and locally finite variation sample path, $\sigma(s)$ is a strictly positive spot volatility process, and $W(s)$ is a standard Brownian motion. The component $k(s)dq(s)$ corresponds to the pure jump component, where $dq(s) = 1$ if there is a jump at time s and 0 otherwise, and $k(s)$ is the jump size. Following this framework, each trading day *i* consists of *M* equally spaced intraday returns where $r_{t,i}$ is the log return of the mid-quote in the interval *t* of the day *i*. The associated test statistic for jumps in $r_{t,i}$ is the absolute return standardised with a jump-robust estimate of the average daily volatility ξ_t together with an intraday volatility factor $f_{t,i}$: $J_{t,i} = \frac{|r_{t,i}|}{\xi_t \, f_{t,i}}$ where ξ_t is estimated as the square root of the realised bipower variation per Barndorff-Nielsen and Shephard (2006) and $f_{t,i}$, is the truncated maximum likelihood periodicity estimate per Boudt et al. (2011). Lee and Mykland (2008) propose to reject the null of no jump on $r_{t,i}$ if: $J_{t,i} > G^{-1}(1-\alpha)S_n + C_n$) where $G^{-1}(1-\alpha)$ is the $(1-\alpha)$ quantile function of the standard Gumbel distribution and $C_n = (2log\, n)^{0.5} - \frac{log\,(\pi) + log\,(\log n)}{2(2log\, n)^{0.5}}$ and $S_n = \frac{1}{(2logn)^{0.5}}$ where *n* is the total number of observations (i.e., M × T). Following Boudt and Petitjean (2014), we reject the null of no jump if $J_{t,i} > S_n\, \beta^* + C_n\; ^{\beta^*}$ with β^* such that $exp\,(-exp\; ^{\beta^*}) = 1-\alpha,\ i.e.\ \beta^* = -log\,(\log(1-\alpha))$ where a is set to 0.01 following Bjursell et al. (2017).

Building on the evidence that expected stock return is a function of average jump size or intensity (Christoffersen et al., 2012), we focus on the size and intensity of jumps. Jump size is measured in terms of price returns and jump intensity is the ratio of the number of 5-minute jumps detected per day to the total number of 5-minute intervals during the trading day. We observe in Panel A in Table 1 that negative jumps generally occur more frequently than positive jumps, while positive jumps tend to be smaller in size and intensity. Interestingly, the average size and intensity of jumps prior to the 2016 Paris climate agreement is approximately 1.3 and 1.2 times, respectively, compared to the post Paris agreement period, suggesting that the climate agreement has had a stabilising effect on jump behaviour in green equities. Finally, the descriptive statistics for the climate factors presented in Panel B highlight the media attention on the discussions, announcements and political appointments that affect climate related policies throughout the sample period, captured by the climate policy factor.

Table 1: Descriptive statistics

Panel A: Intraday Jumps				
		Whole sample	Pre-Paris agreement	Post-Paris agreement
Number of Jumps		5,183	4,683	500
(+) Jumps		2,534	2,303	231
(–) Jumps		2,649	2,380	269
Jump Intensity		0.034	0.036	0.027
(+) Jumps		0.016	0.018	0.011
(–) Jumps		0.017	0.018	0.013
Jump Size		0.318	0.327	0.267
(+) Jumps		0.315	0.321	0.271
(–) Jumps		-0.322	-0.331	-0.261
Panel B: Climate Risk Proxies				
	Mean	Std.	Min	Max
Climate Policy	0.740	1.031	0.000	10.856
International Summit	0.477	0.799	0.000	11.959
Global Warming	0.383	0.600	0.000	9.218
Natural Disaster	0.286	0.508	0.000	5.195

Notes: Panel A reports the descriptive statistics of 5-minute price jumps for the Invesco Global Clean Energy ETF, obtained from intraday returns over the Jun 2007 – Nov 2019 period. Jump test statistic is computed following Lee and Mykland (2008). Jump size is the corresponding return when a jump is identified by the jump statistic. Jump intensity is the ratio of the number of 5-minute jumps detected per day to the total number of 5-minute intervals during the trading day (9:30 – 4 pm). 2016 is used as the cutoff year when the Paris Agreement was signed. Panel B reports the descriptive statistics for daily climate risk proxies, namely climate policy, international summits, global warming and natural disasters.

2.1 Methodology

In order to explore the dynamic predictive relationship between climate risk and jumps, we begin our analysis by examining time-varying causality running from each climate measure via the framework of Shi et al. (2020). Let y_t be a k-vector time series of jump measures generated by the process $y_t = y_0 + \alpha y_1 t + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t$. The Granger causality test for a possible integrated variable y_t is conducted via a lag augmented VAR suggested by Dolado and Lütkepohl (1996) in the form.

$$Y = \tau\Gamma' + X\Theta' + B\Phi' + \varepsilon \,, \tag{2}$$

where $Y = (y_1, \ldots, y_T)_{T*n'}, \tau = (\tau_1, \ldots, \tau_T)_{t*2'}, \tau_t = (1, t)_{2*1'}, X = (x_1, \ldots x_T)_{T*np'}, x_t = (y_{t-1'}, \ldots, y_{t-p'})_{np*1'}$ $\Theta = (\beta_1, \ldots, \beta_p)_{n*np}, B = (b_1, \ldots, b_T)_{T*nd'}, b_t = (y_{t-p-1'}, \ldots, y_{t-p-d'})_{nd*1'}, \Phi = (\beta_{p+1}, \ldots, \beta_{p+d})_{n*nd}$ and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_T)_{T*n'}$ and d is the maximum order of integration for y_t. The test employs the Wald statistic over $[\ f_1, f_2\ ]$ with a sample size fraction of $f_w = f_2 - f_1 \geq f_0$, formulated as $SW_f(f_0) = \frac{sup}{(f_1,f_2)\in\Lambda_0, f_2=f}\{W_{f_2}(f_1)\}$, where $\Lambda_0 = \{(f_1, f_2): 0 < f_0 + f_1 \leq 1 \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for some minimal sample size $f_0 \in (0,1)$ in the regressions. In our application, following Shi et al. (2020), we employ the recursive evolving window algorithm as the most reliable approach to detect causality.

In addition to time-varying causality analysis, we also adopt a direct approach to examine the in- and out-of-sample predictive relationships. In-sample predictability is assessed via

$$y_{t+1} = \alpha_0 + \alpha_1 y_t + \alpha_2 cp_t + \alpha_3 is_t + \alpha_4 gb_t + \alpha_5 nd_t + \varepsilon_t \tag{3}$$

where y_{t+1} is the respective jump statistic (size and intensity) on day *t+1* and *cp*, *is*, *gb*, and *nd* are the lagged climate risk proxies associated with climate policy, international summits, global warming and natural disasters, respectively. A similar approach is also used to assess out-of-sample predictability by comparing forecasting models that include each climate predictor against the benchmark model that excludes them. To evaluate the forecasts of competing models, we adopt the model confidence set (MCS) methodology of Hansen et al. (2011) wherein we rank the models based on three loss functions, $MSE = N^{-1}\sum_{t=1}^{N}(J_t - \hat{J}_t)^2$, $HMSE = N^{-1}\sum_{t=1}^{N}(\ 1 - \frac{\hat{J}_t}{J_t})^2$ and $HMAE = N^{-1}\sum_{t=1}^{N}|1 - \frac{\hat{J}_t}{J_t}|$, where $\hat{J}_t$ denotes the out-of-sample jump forecast obtained from the respective model and N is the length of out-of-sample evaluation period[1]. This approach has been widely applied in the literature to evaluate the out-of-sample prediction performance of volatility models (e.g. Bauwens and Otranto, 2016; Koopman et al., 2016; Niu et al., 2023). Following the literature, we select the range-based (Range) and semi-quadratic (SemiQ) statistics as the MCS statistics and compute their p-values using a bootstrap program. The Range and SemiQ statistics are formulated as:

$$T_R = \underset{u,v\,\epsilon\, M}{\text{MAX}} \frac{|\bar{d}_{i,uv}|}{\sqrt{var(d_{i,uv})}},\ T_{SQ} = \underset{u,v\,\epsilon\, M}{\text{MAX}} \frac{(\bar{d}_{i,uv})^2}{var(\bar{d}_{i,uv})},\ \bar{d}_{i,uv} = n^{-1}\sum_{t=1}^{n}\bar{d}_{i,uv}, t \tag{4}$$

where $\bar{d}_{i,uv}$ is the relative sample loss statistic which measures the relative sample loss between the i^{th} and j^{th} models. Given that each model has a p-value in an initial set of competing models, the MCS test selects models with superior predictive performance based on the criterion of p-values greater than 0.10.

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[1] MSE, HMSE and HMAE denote the mean squared-error, heteroskedasticity-adjusted MSE and mean absolute error (MAE), respectively.

3. Empirical results

Figures 1 and 2 plot the results of causality running from each climate risk measure to jump size and intensity, respectively. Note that the daily climate measures reflect the intensity of news coverage for climate-related events. While the natural disasters and global warming factors capture the occurrence of natural disasters and the rise in temperatures driven by rising emissions, respectively, the international summits and climate policy factors capture international events and policy related discussions related to climate change, respectively. We observe significant causality running from all climate risk proxies to jump size in Figure 1. International summits along with natural disasters have a particularly strong causal effect on jump size as well as its positive and negative variations in Figures A1 and A2 in the Appendix.

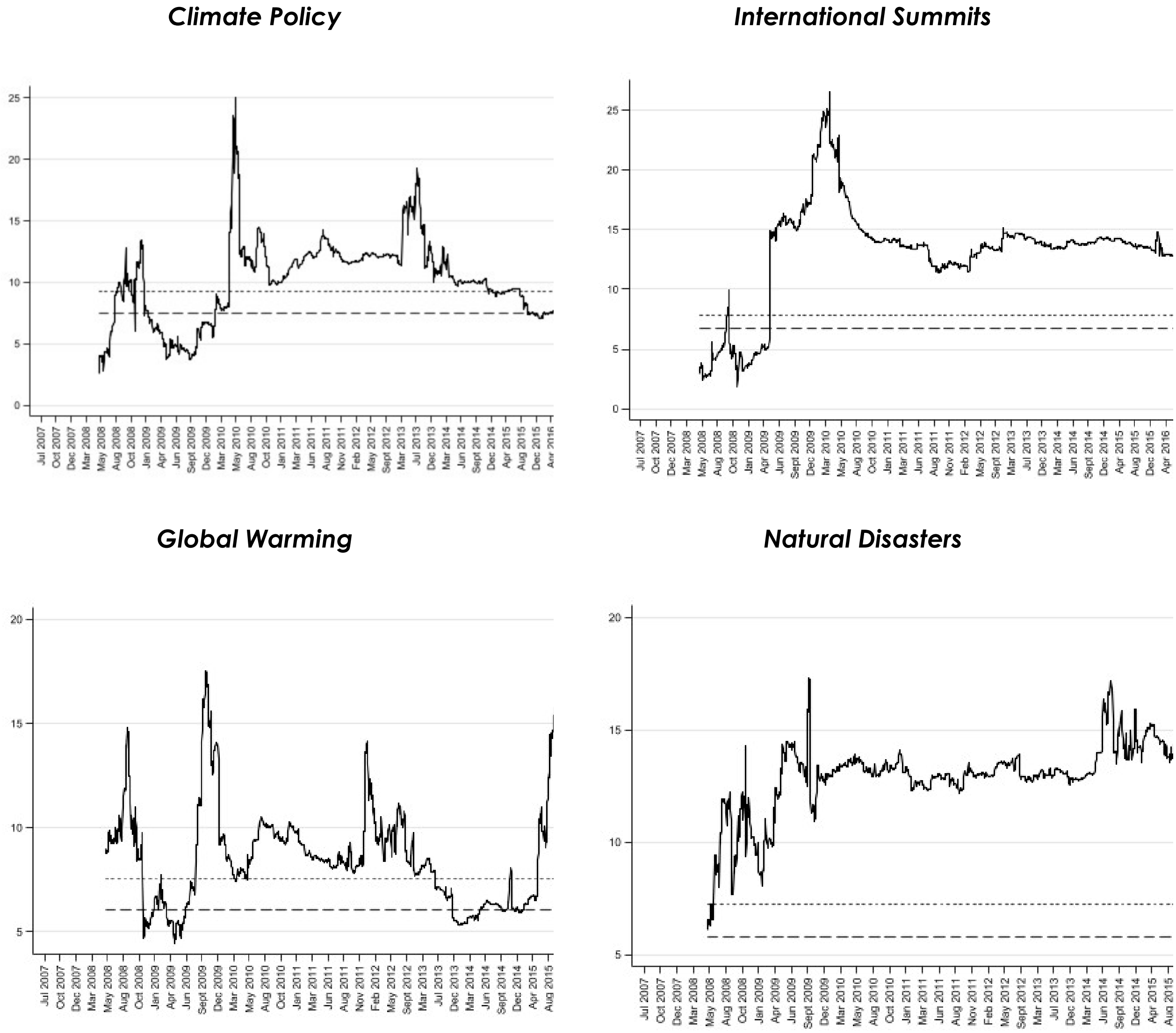
We observe in Figure 1 a significant rise in causal effects on both jump measures in late 2009 following the publication of the climate report by the U.N. Panel on Climate Change (December 2009). This period also coincides with BP oil spill in the Gulf of Mexico (April 2010) which is highlighted by a rise in causality from natural disasters to jump size in particular. The predictive power of international summits and natural disasters could be explained by the bad news they capture regarding new regulations on pollutants and rising public attention to climate events, respectively. The causal effect of international summits on positive jump size in Figure A1 is particularly evident starting with late 2012 when the U.S. climate extremes index doubled and 50% of U.S. counties were named as disaster areas[2]. Considering that international summits mostly relate to the introduction of a global tax on pollution, we argue that bad news that relate to brown industries serve as a driver of positive jumps in green assets.

A similar predictive pattern is also observed for jump intensity in Figure 2 where international summits are found to have a consistent causal effect on the intensity of jumps in both directions (Figures A3 and A4). In the case of global warming, Faccini et al. (2023) observe that this factor can be related to less often to a significant event. In our case, we observe a significant rise in causality running from global warming to jump size in particular during mid to late 2009 which again coincides with the publication of the climate report by the U.N Panel on Climate Change. The causal effects of global warming on the intensity of jumps, however, is found to be largely insignificant. Overall, our finding show that strong causal effects are present driven particularly from measures of transition climate risks to both jump measure, in line with the recent evidence by Faccini et al. (2023) that transition climate risk is a dominant driver of stock returns as investors price the risk of government intervention in their trades of these assets. From an investment perspective, considering the evidence that jumps serve as a systematic risk factor in expected stock returns (Dunham and Friesen, 2007), our findings suggest the presence of a climate policy related risk premium in stock returns through its effect on jump dynamics.

[2] https://www.wri.org/insights/look-back-2012-year-extreme-weather-events

Figure 1: Time varying causality between climate risk and jump size in green assets.

Jump Size

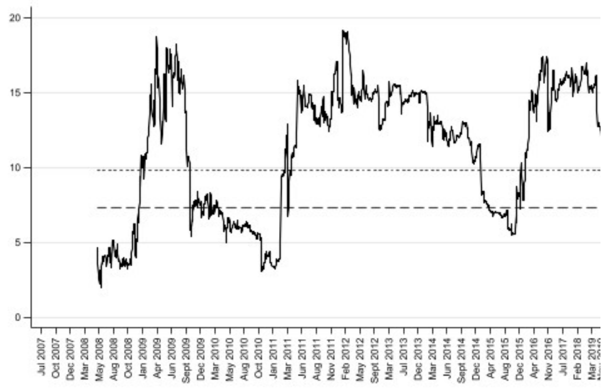


Notes: This figure presents the recursive expanding Wald test statistics (in the y-axis) for Granger-causality from each climate uncertainty measure to jump size. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

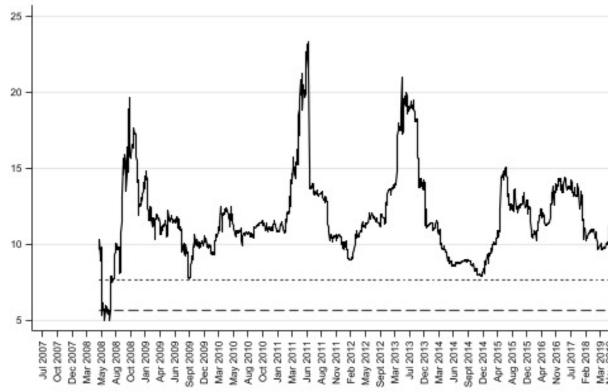
Figure 2: Time varying causality between climate risk and *jump intensity* in green assets.

Jump Intensity

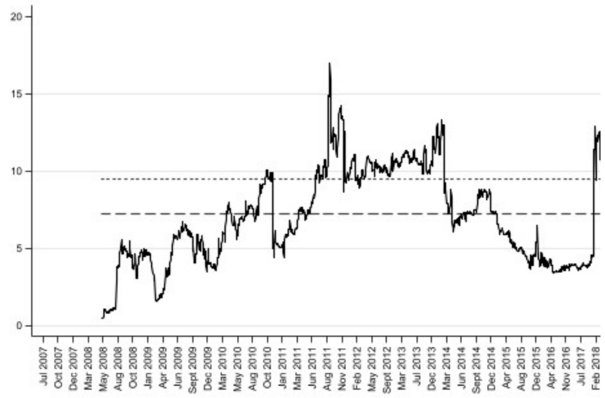
Climate Policy



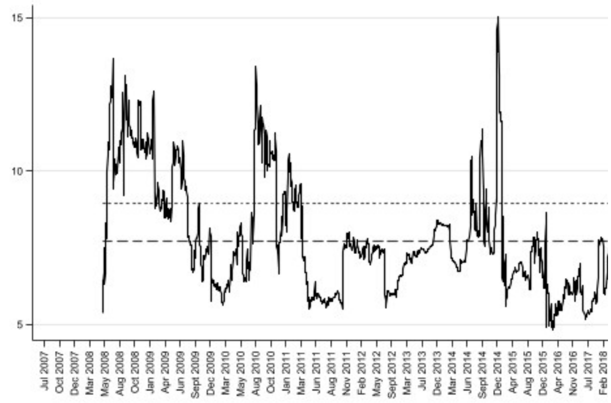
International Summits



Global Warming



Natural Disasters



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

The in-sample predictability results reported in Table 2 further support the predictive power of transition risks over both the jump size and intensity. We find that greater climate policy and international summits factors predict higher jump size and intensity, while they negatively predict the occurrence of negative jumps. Considering that an increase in the international summits factor signals bad news for the economy as the main implication of these meetings is a possible global tax on pollutants, this means that bad news for the economy in transition drives the intensity and size of positive jumps in green assets. Although a rise in the climate policy factor can signal good or bad news for investors depending on the political tendency of the governing party, our findings show that increased uncertainty surrounding policy actions also drives jump dynamics in green stocks.

Table 2: In-sample predictability of jumps

	Jump Size	Positive Jump Size	Negative Jump Size	Jump Intensity	Positive Jump Intensity	Negative Jump Intensity
α_0	0.00277***	0.00279***	-0.00287***	0.03100***	0.02140***	0.02200***
	(0.00009)	(0.00011)	(0.00014)	(0.00072)	(0.00058)	(0.00060)
Climate Policy	0.00022***	0.00026***	-0.00017**	0.00160***	0.00082**	0.00031
	(0.00005)	(0.00006)	(0.00007)	(0.00041)	(0.00032)	(0.00032)
International Summit	0.00039***	0.00030***	-0.00038***	0.00190***	0.00010	0.00080
	(0.00008)	(0.00010)	(0.00012)	(0.00066)	(0.00050)	(0.00053)
Global Warming	-0.00008	-0.00019	-0.00003	0.00090	-0.00040	0.00080
	(0.00010)	(0.00012)	(0.00015)	(0.00082)	(0.00062)	(0.00069)
Natural Disaster	0.00008	0.00020	-0.00014	0.00050	0.00120	0.00040
	(0.00011)	(0.00015)	(0.00017)	(0.00096)	(0.00076)	(0.00077)

Notes: This table presents the results for $y_{t+1} = \alpha_0 + \alpha_1 y_t + \alpha_2 cp_t + \alpha_3 is_t + \alpha_4 gb_t + \alpha_5 nd_t + \varepsilon_t$ where y_{t+1} refers to the respective jump measure (in each column) on day t+1 and cp, is, gb, and nd are the lagged climate risk proxies for climate policy, international summits, global warming and natural disasters, respectively. Standard errors are reported in parentheses. ***,**,* represent significance at 10, 5 and 1 percent, respectively.

Further extending our analysis to out-of-sample predictability, we find in Table 3 that the predictive power of climate policy and international summits extends to out-of-sample as well. The results show that climate policy and international summits provide the most accurate out-of-sample performance to predict the size of jumps. While international summits provide greater predictive contribution for positive jumps as they signal bad news for brown industries, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies due to the information content they capture regarding regulation changes. In the case of jump intensity, we find that climate proxies show out-of-sample performance for the signed components only with climate policy as the most dominant predictor of positive jump intensity as it captures bad news for brown industries with respect to taxation of pollutants. Natural disasters also stand out over positive jump intensity forecasts, likely as an increase in this factor signals greater concern by the public and bad news for the economy overall. In contrast, both climate policy and international summits stand out with the best out-of-sample predictive performance for negative jump intensity. Overall, our findings show that transition climate risk measures, captured by the markets' concerns regarding climate policy and international summits, possess significant predictive information regarding the size and direction of price jumps, both in- and out-of-sample.[3]

[3] Based on a comment from an anonymous reviewer, we replicated our analysis for another green ETF, namely the First Trust Nasdaq Clean Edge Green Energy Index Fund, and observed similar results confirming the predictive role of transition climate factors on jumps. Likewise, controlling for market volatility in the models yields qualitatively similar inferences (available upon request).

Table 3: **Out-of-sample predictability of jumps**

	Range-based (Range) MCS statistic			Semi-quadratic (SemiQ) MCS		
	MSE	HMAE	HMSE	MSE	HMAE	HMSE
			Jump Size			
Benchmark	**0.20780**	0.00000	0.00000	**0.28060**	0.00000	0.00000
Climate Policy	**0.31320**	0.00000	0.00120	**0.43060**	0.00000	**0.00100**
International Summit	**1.00000**	**0.11340**	**0.28940**	**1.00000**	**0.11340**	**0.28940**
Global Warming	**0.04220**	0.00000	0.00000	**0.14440**	0.00000	0.00000
Natural Disaster	**0.04220**	0.00000	0.00020	**0.11220**	0.00000	0.00000
			Positive Jump Size			
Benchmark	0.01220	0.00000	0.00000	0.00840	0.00000	0.00000
Climate Policy	**0.17200**	0.00000	0.00060	**0.22320**	0.00000	**0.00120**
International Summit	**0.31300**	0.00960	0.05500	**0.31300**	0.00960	0.05500
Global Warming	0.07740	0.00000	0.00000	0.06200	0.00000	0.00020
Natural Disaster	0.01600	0.00000	0.00000	0.01120	0.00000	0.00020
			Negative Jump Size			
Benchmark	**0.16940**	0.00000	0.00000	**0.28820**	0.00000	0.00000
Climate Policy	**0.95100**	0.00260	**0.60400**	**0.94400**	0.00220	**0.60400**
International Summit	**0.95100**	0.00260	**0.48300**	**0.94400**	0.00140	**0.38220**
Global Warming	**0.10000**	0.00000	0.00000	**0.14080**	0.00000	0.00160
Natural Disaster	**0.16940**	0.00000	0.01820	**0.21520**	0.00020	0.01620
			Jump Intensity			
Benchmark	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Climate Policy	0.04640	0.00000	0.00000	0.05180	0.00020	0.00080
International Summit	0.04640	0.00700	0.01520	0.05180	0.00700	0.01520
Global Warming	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Natural Disaster	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
			Positive Jump Intensity			
Benchmark	0.00880	0.00000	0.00000	0.09640	0.00000	0.00000
Climate Policy	**1.00000**	**1.00000**	**1.00000**	**1.00000**	**1.00000**	**1.00000**
International Summit	**0.22220**	0.00060	0.00020	**0.41720**	0.02740	0.00560
Global Warming	0.00880	0.00000	0.00000	0.04380	0.00000	0.00000
Natural Disaster	**0.57100**	**0.17720**	**0.10020**	**0.57000**	**0.15700**	0.10360
			Negative Jump Intensity			
Benchmark	0.00040	0.00000	0.00000	0.00080	0.00000	0.0000
Climate Policy	**0.83620**	**0.27600**	**0.16780**	**0.83620**	**0.23300**	**0.1226**
International Summit	**0.39060**	**0.27600**	**0.16780**	**0.32020**	**0.23180**	**0.1206**
Global Warming	0.00820	0.00020	0.00000	**0.02180**	0.00300	0.0006
Natural Disaster	0.00040	0.00000	0.00000	0.00360	0.00000	0.0000

Notes: This table presents the model confidence set (MCS) p-values based on the range-based (Range) and semi-quadratic (SemiQ) test statistics, T_R and T_{SQ}. In each panel, the benchmark model that excludes the climate predictors (represented in shaded rows) is tested against the extended models that incorporate each climate risk proxy, respectively. MSE, HMSE and HMAE denote the mean squared-error, heteroskedasticity-adjusted MSE and mean absolute error (MAE), respectively. Models with p>0.10 are indicated in bold. We follow a 75% in-sample and 25% out-of-sample split.

4. Conclusion

This paper shows that climate risk can help predict the size and direction of intraday jumps in green assets, both in and out-of-sample. Transition climate risk proxies including international summits and climate policy are found to be the most dominant predictors compared to proxies of physical climate risks. While international summits that capture bad news for brown industries regarding the taxation of pollutants provide the greatest predictive contribution for positive jumps in green assets, both climate policy and international summits are better predictors for negative price jumps, compared to physical climate proxies. Our findings provide novel insight to the role of climate risk as a driver of idiosyncratic tail risk and jump innovations in green assets and imply that asset pricing models that incorporate jump risk as a risk factor can be improved by exploiting the predictive relationship between jumps and climate risk. The results pave the way for pricing models in green equities that incorporate jump risk as a function of climate risk.

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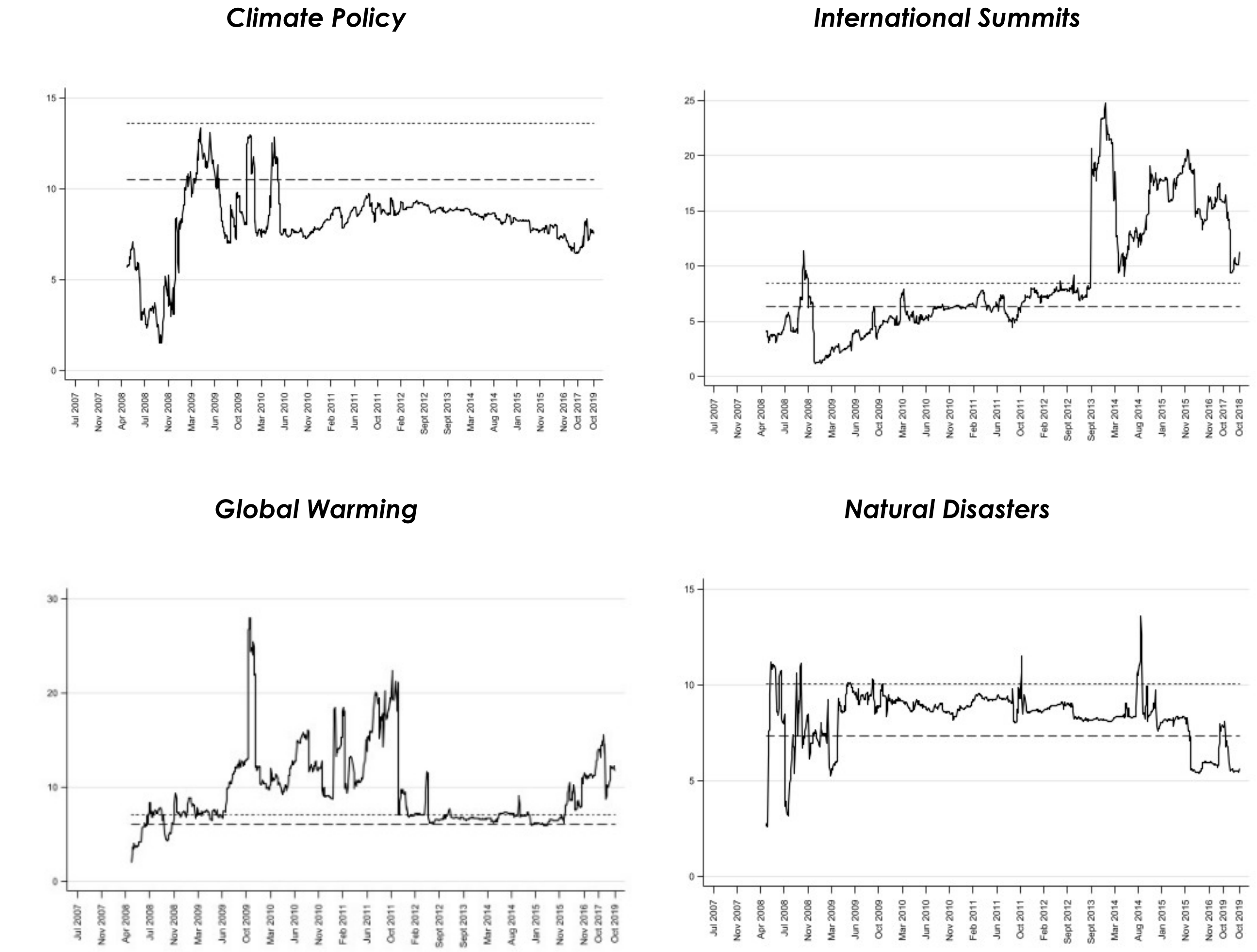
Appendix

Figure A1: Time varying causality between climate risk and *positive jump size*.

Positive Jump Size

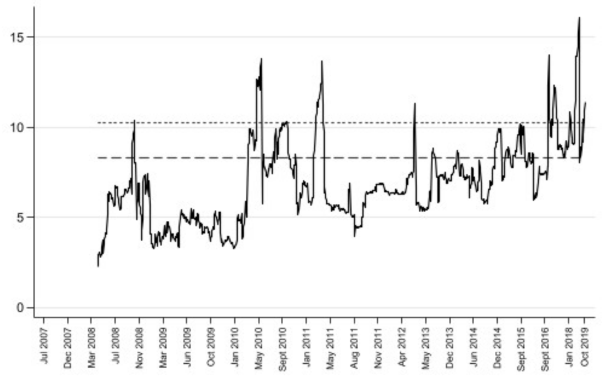


Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *positive jump size*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

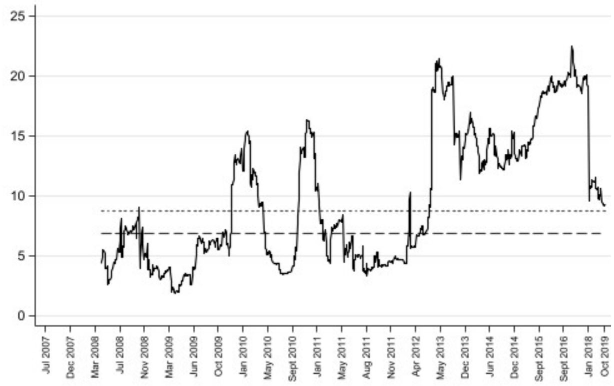
Figure A2: Time varying causality between climate risk and *negative jump size*.

Negative Jump Size

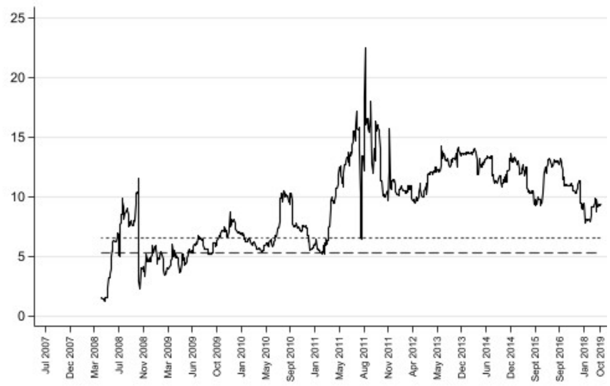
Climate Policy



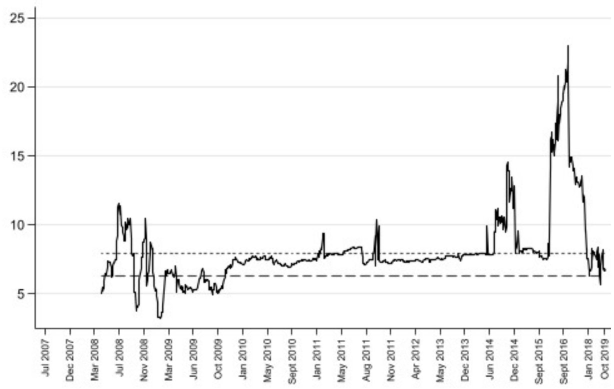
International Summits



Global Warming



Natural Disasters

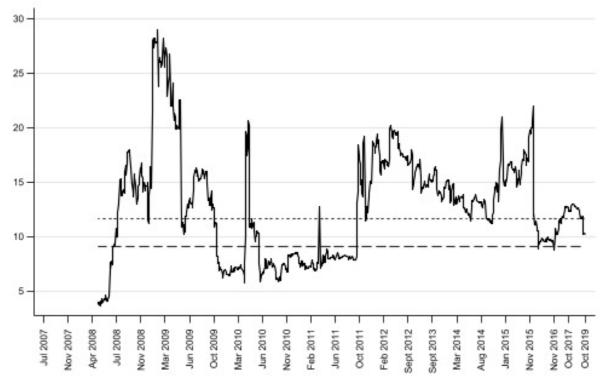


Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *negative jump size*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

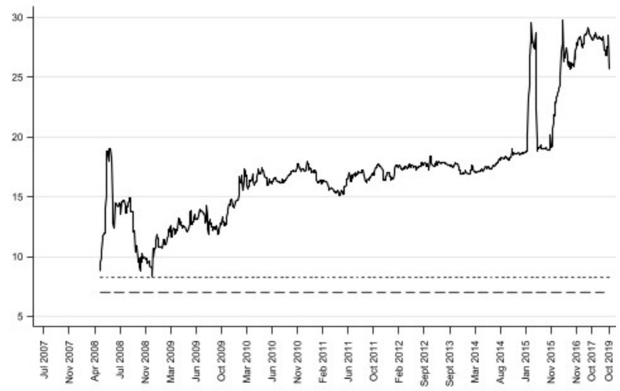
Figure A3: Time varying causality between climate risk and *positive jump intensity*.

Positive Jump Intensity

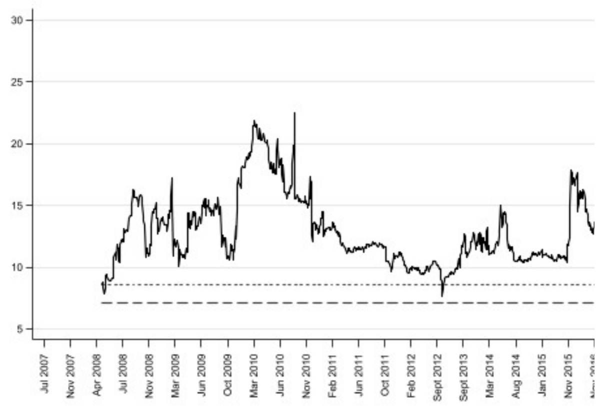
Climate Policy



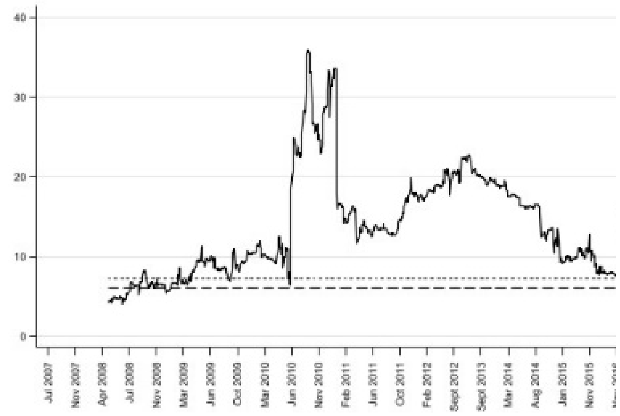
International Summits



Global Warming



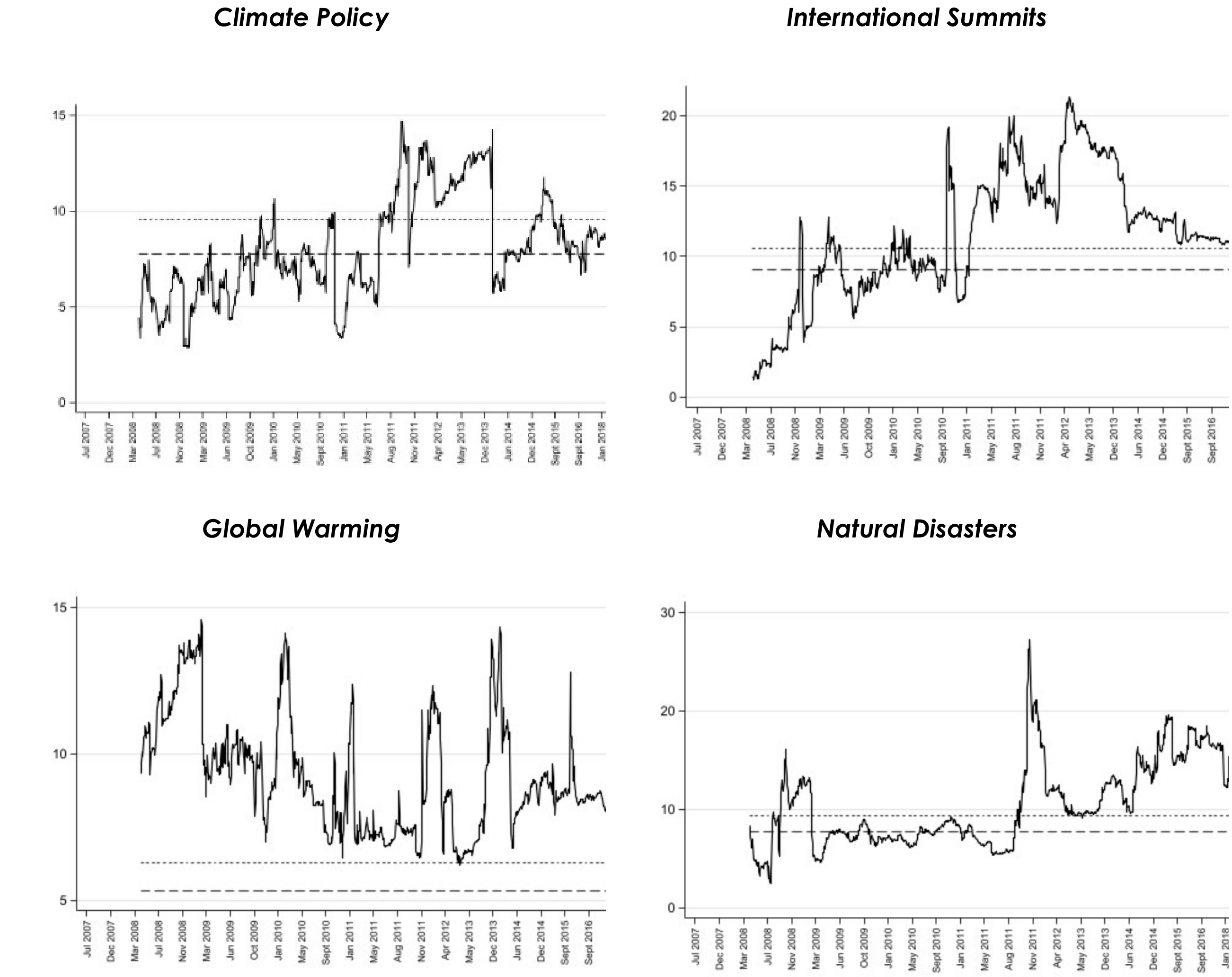
Natural Disasters



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *positive jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.

Figure A4: Time varying causality between climate risk and *negative jump intensity*.

Negative Jump Intensity



Notes: This figure presents the recursive expanding Wald test statistics (in the vertical axis) for Granger-causality from each climate uncertainty measure to *negative jump intensity*. Dashed lines represent the 90th (--) and 95th (-) percentile of bootstrapped test statistics.