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Do Climate Risks Predict US Housing Returns and Volatility? Evidence from a Quantiles-Based Approach

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Abstract

We analyse the ability of textual-analysis-based daily proxies of physical (natural disasters and global warming) and transition (US climate policy and international summits) climate risks to predict daily movements in the US housing market over the period 2nd August, 2007 to 29th November, 2019. To this end, we apply a nonparametric causality-in-quantiles test not only to uncover potential predictability in the entire conditional distribution of housing returns and volatility but also to account for nonlinearity and structural breaks which exist between housing returns and climate risk factors. We find that climate risk factors (and the associated uncertainty) do predict housing returns and volatility across the conditional distribution. These results are robust to alternative daily data of aggregate housing prices for the US and ten major metropolitan statistical areas (MSAs). Insights from our findings can benefit academics, investors, and policymakers in their decision-making.

Keywords: Physical and transitional climate risks; US housing returns and volatility; higher-order nonparametric causality-in-quantiles test; natural disasters and global warming; US climate policy and international summits

JEL Codes: C22; C32; Q54; R30

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1. Introduction

Climate change involves physical and transitional risks. The former is associated with rising temperatures, higher sea levels, more destructive storms, and floods or wildfires. The latter stems from the gradual transition to a low-carbon economy involving climate policy changes, the emergence of competitive green technologies, and shifts in consumer preferences. Naturally, though the level and form of the underlying uncertainty may vary, every scenario in the future includes climate-related financial risks. Hence, unsurprisingly, climate-related risks adversely affect a large number of asset classes including equities (Bouri et al., 2022), fixed-income securities, real estate, and even financial institutions (Battiston et al., 2021; Flori et al., 2021; Giglio et al., 2021).

The prominence of the housing market in the United States (US) cannot be overstated. US residential real estate represents about 84.18% of total household non-financial assets, 29.55% of total household net worth, and 26.27% of household total assets (Financial Accounts of the US, First Quarter, 2022)[1]. In light of the importance of the US housing market, and the reality of climate change, recent studies have analysed the climate risks-real estate price nexus in the US. In this regard, evidence of negative effects on local housing market prices has been detected for sea-level rises (Giglio et al., 2015; Murfin and Spiegel, 2020; Shi and Varuzzo, 2020), flooding risk (Votsis and Perrels, 2016; Keenan et al., 2018; Bernstein et al., 2019; Baldauf et al., 2020; Yi and Choi, 2020), wildfire risk (McCoy and Walsh, 2018; Garnache and Guilfoos, 2019), abnormal temperatures (Livy, 2020; Gourley, 2021), and hurricane and tornado activity (Donadelli et al., 2020; Fang et al., 2021). While these studies are indeed insightful, they are conducted using event study-based approaches focusing on specific regions and/or low-frequency (monthly, quarterly, or annual) data.

In this paper, we extend this growing literature by analysing, for the first time, the predictive ability of the information derived from textual-analysis-based daily proxies of physical (natural disasters and global warming) and transition (US climate policy and international summits) climate risks, for not only daily housing returns but also the volatility of the CME-S&P/Case-Shiller House Price Index (HPI) Continuous Futures (CS CME). House price movements are known to lead US business cycles historically (Balcilar et al., 2014; Nyakabawo et al., 2015;

[1] The reader is referred to Table B.101, which shows the balance sheet of households and non-profit organizations, in https://www.federalreserve.gov/releases/z1/20220609/z1.pdf for further details.

Emirmahmutoglu et al., 2016), and information about where housing prices are headed on a daily basis is valuable to policymakers for understanding the future path of monthly and quarterly real activity variables using mixed-frequency models (BańBura et al., 2011), and undertaking appropriate policy responses to prevent possible recessions (Aye et al., 2022). Moreover, high-frequency predictability of housing returns and volatility helps investors make timely portfolio allocation decisions by capturing the "true risk" of the housing market (Bollerslev et al., 2016; Nyakabawo et al., 2018; Segnon et al., 2020).

Due to the existence of nonlinearity, and the regime changes which come with macroeconomic uncertainty stemming from climate risk factors, we control for the resulting misspecification by using the *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al. (2018). The advantage of this model is that it tests the predictability of housing returns and volatility over their entire conditional distribution. Furthermore, given the heterogeneous nature of the US housing market (Gupta et al., forthcoming), and various parts of the country being subjected to a varying degree of climate risk (Gil-Alana et al., forthcoming), we also conduct a robustness check based on daily S&P CoreLogic Case-Shiller home price indexes available for ten major metropolitan statistical areas (MSAs), namely Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco and Washington, and the associated weighted average, to obtain a ten-city composite index.

Our analysis shows strong evidence supporting the predictive power of physical and transition climate risks for the returns and volatility of the US housing market across various quantiles. The causality-in-quantiles results show that climate risks cause both housing returns and volatility over all the quantiles of the conditional distribution, with the strongest effect at the lowest quantile (0.10). These results are robust to alternative data on aggregate and regional house prices as well as various measures of physical and transitional climate risks.

The remainder of the paper is organized as follows: Section 2 outlines the methodology. Section 3 describes the dataset and presents the results arising from the main analysis and the various robustness analyses. Section 4 concludes the paper.

2. Econometric Methodology

In this section, we provide a brief overview of the *k*-th order nonparametric causality-in-quantiles approach. Balcilar et al. (2020, 2021), and Bouri et al. (2021) apply this approach to analyse the effects of mortgage default risks, sentiment, and uncertainty on high-frequency housing price movements for both the first and second order (returns and volatility). Balcilar et al. (2018) developed this methodology for testing nonlinear Granger causality using a hybrid approach, based on the work of Nishiyama et al. (2011) and Jeong et al. (2012).

Let y_t denote housing returns and x_t the metric of a particular type of climate risk, details of which we discuss below in the data segment. Furthermore, 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 $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$.

Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

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

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

Jeong et al. (2012) show that the feasible kernel-based test statistics have the following format:

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

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, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by:

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

with $L(\bullet)$ denoting the kernel function.

Balcilar et al. (2018) extend the framework of Jeong et al. (2012), based on Nishiyama et al. (2011), to the *second* (or higher) moment which allows us to test the causality between a specific climate risk and housing returns volatility. In this case, the null and alternative hypotheses are given by:

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

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

The causality test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. Balcilar et al. (2018) indicate that a rescaled version of $\hat{J}_T$ has a standard normal distribution. The testing approach is sequential and failing to reject the test for $k=1$ does not automatically lead to no causality in the *second* moment; one can still construct the test for $k=2$.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order based on the Schwarz information criterion (SIC), and determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Data and Results

3.1. Data

For climate risks, we use the measures constructed by Faccini et al. (2021) who employ the latent Dirichlet allocation (LDA) technique of Blei et al. (2003), an unsupervised textual analysis method, to dissect the multifaceted nature of climate-change risks and construct corresponding factors. They apply LDA to articles that contain the words "climate change" and "global warming", published in Thomson Reuters News Archive, and then give every topic an economic interpretation. Furthermore, they compute a time series of the topic shares (that is, the proportion of an article's text associated with a given topic) that represent how news coverage evolves over time for any given topic. Finally, Faccini et al. (2021) identify four major climate-related topics of interest: the occurrence of natural disasters; the role of emissions in relation to global warming; U.S. climate policy; and international climate-change summits. The time series of the four climate-related topics are treated as climate-risk factors because their fluctuations signal future effects on the economy.[2]

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[2] The data is freely available for download from the website of Dr. Renato Faccini at: https://sites.google.com/site/econrenatofaccini/home/research?authuser=0.

For daily house prices, from which housing log-returns (HR) are computed,[3] we use the CME-S&P/Case-Shiller HPI Continuous Futures (CS-CME) derived from Refinitiv Datastream. Our sample is from 2nd August, 2007 to 29th November, 2021. We thus have 3,105 observations, based on data availability of the variables under consideration.[4]

HR and the four measures of climate risks are summarized in Table A1 and plotted in Figure A1 in the Appendix to the paper. As can be seen from Table A1, HR is negatively skewed and has excess kurtosis, implying a non-normal distribution. The Jarque-Bera test also overwhelmingly rejects the null of normality. This provides a preliminary justification for using a quantiles-based approach.

3.2. Empirical results

As a preliminary test, and for completeness and comparability, we conduct the standard linear Granger causality tests for the predictability of HR due to the four metrics of climate risks, using SIC-based lag-length criteria. As can be seen from Table 1, the resulting $\chi^2(p)$ statistics indicate that the null hypothesis that a particular climate risk does not Granger cause HR can only be accepted for the case of international summits at the 1% level of significance, with weak evidence (at the 10% level of significance) of the same for global warming. Surprisingly, no predictability arises from natural disasters or US climate policy. However, this preliminary evidence is based on the conditional mean-based test. It does not provide any information on causality at various quantiles of the conditional distribution of HR. The standard causality framework is also silent about the predictability of the variance of HR.

[INSERT TABLE 1]

More importantly, the results from the linear model could suffer from misspecification due to nonlinearity and structural breaks in the relationship between climate risks and HR, which are general observations when dealing with high-frequency data. We formally test for the presence of nonlinearity by applying the Brock et al. (1996) (BDS) test, which considers the residuals from the autoregressive specification with the lag length chosen using SIC. For testing structural breaks, we use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003). The

[3] By using the log-returns, we ensure that the housing data is mean-reverting. The climate risk measures are stationary at levels. The results of the augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1979) of stationarity (see Table A1) indicate the stationarity of housing returns and climate risk-related data at the 1% level, which meets the data requirements of the Granger causality test.

[4] Note that the climate risk data actually goes as far back as 3rd January, 2000.

presence of these two issues motivate us to use the nonparametric quantiles-in-causality approach of Balcilar et al. (2018). As shown in Table 2, we reject the null hypothesis of *i.i.d.* residuals, at various embedded dimensions (m), at a 1% significance level for all climate risk factors. Thus, there are nonlinearities in the relationship between climate risks and housing returns. For the Bai and Perron (2003) test for structural breaks, we allow for heterogeneous error structures, with 15% trimming. Again, we test for the autoregressive specification with SIC-based p lags for each equation. We detect one break, i.e., 5th August, 2009 in the case of US climate policy, global warming and natural disasters, but as many as five breaks (17th June, 2009; 14th March, 2012; 2nd May, 2014; 22nd March, 2016; 26th January, 2018) when dealing with international summits.

The 2009 break dates likely correspond to the end of the financial crisis, with the housing market recovering from the crash. In June 2009, the House of Representatives passed a bill to address the threat of climate change[5], while the El Niño Southern Oscillation (ENSO) shifted from a neutral to an El Niño state (NOAA, July 2009). In August 2009, there were almost 8,000 wildfires, with 1.6 million acres of land burning (NOAA, September 2009), which could cause the futures data to reflect the risk associated with investment in property. The 2012, 2014, 2016, and 2018 break dates likely reflect policy decisions emanating from the annual United Nations Climate Change conference of the previous year (typically held at the end of the year), and the housing futures reacting to these policies. On 22nd April, 2016, the Paris Agreement was signed, as a result, the 2016 break potentially reflects the market's anticipation of this resolution to reduce emissions, i.e., impact due to transitional risks.

[INSERT TABLE 2]

These results justify the use of the causality-in-quantiles test approach. This approach is robust to misspecification due to its nonparametric nature. It also allows us to test the predictability of HR due to climate risks, not only for returns but also for volatility over their respective conditional distributions. In other words, the linear Granger causality test results are not necessarily reliable, besides being limited in their information content. Table 3 reports the results of the causality-in-quantiles test for housing returns and volatility, emanating from US climate policy, international summits, global warming, and natural disasters, considered one-by-one, over the quantile range 0.10 to 0.90, with a quantile increment of 0.10, giving us an analysis for nine conditional quantiles. The results for returns (as given by Pane A of Table 3)

[5] See: https://www.nytimes.com/2009/06/27/us/politics/27climate.html.

show that all climate risks cause HR at a 1% significance level over all the quantiles of the conditional distribution considered. The strongest effect is felt at the lowest quantile (0.10). The results for volatility (given by Panel B) tell a similar story. Stated differently, all four climate risks cause both housing returns and volatility, across all their respective states, unlike what is observed from the linear causality test.

[INSERT TABLE 3]

Considering that investors tend to herd in the housing market during bullish periods (Ngene et al., 2017), the declining strength of the predictability of housing returns and volatility (as measured by squared returns) due to climate risks in higher quantiles is not surprising. This implies that economic agents tend to improve their investment positions during bearish housing returns, and phases of lower volatility (risk)[6], by taking the information content of climate risks-related factors.

Besides the four climate-risk factors, Faccini et al. (2021) also obtain a fifth factor by performing a narrative analysis on the textual factor to identify the content of US climate change news. The authors select articles with a loading on the domestic policy topic greater than 40%, and mark it with a +1 if it signals an increase in transition risks, with a −1 if it suggests a fall, and with a zero if its content is mixed. Then, a time series is constructed by summing the marks given to the articles over each day. When we use this narrative factor and reconduct our k-th order nonparametric causality-in-quantiles test for housing returns and squared housing returns, we obtain qualitatively similar results to those for the four other climate risk factors, as reported in Table 3.

To test the robustness of our results, we evaluate the effect of climate risks on an alternative dataset of daily housing prices, specifically the series constructed by Bollerslev et al. (2016). Thus, we analyse the ability of climate risks to predict house price returns in ten US metropolitan statistical areas (MSAs). We calculate the daily composite housing index ($P_{c,t} = \sum_{i=1}^{10} w_i \, P_{i,t}$) of Wang (2014) as a proxy for aggregate US housing price, a weighted average of the ten MSAs. Their respective weights (w_i) are: Boston (0.212), Chicago (0.074), Denver (0.089), Las Vegas (0.037), Los Angeles (0.050), Miami (0.015), New York (0.055), San Diego

[6] Unreported results show that the significant positive relationship between US housing returns shocks and (conditional) volatility is confirmed based on asymmetric GARCH models such as the exponential GARCH (EGARCH) (Nelson, 1991) and GJR (Glosten et al., 1993) models. These results are available upon request from the authors.

(0.118), San Francisco (0.272), and Washington D.C. (0.078). These represent the total aggregate values of housing stock in the ten MSAs in the year 2000 (Wang et al., 2014). The causality-in-quantiles results for US climate policy, international summits, global warming, and natural disasters on the housing returns and volatility of aggregate US and the ten MSAs[7] are given in Tables 4(a) and 4(b). Generally, the four climate risk factors are found to be a predictor of not only national but also regional housing returns and volatility in particular, again, as with futures data, with stronger evidence of predictability observed at lower quantiles.

[INSERT TABLE 4]

Taken together, our results are robust to the use of alternative data on aggregate and regional house prices. Furthermore, they are robust to the use of various measures of physical and transitional climate risks, with strong evidence of return and volatility predictability of US housing data.

4. Conclusion

Recently, a growing number of studies relate climate risks with the first-moment movements of US housing prices and/or returns using event study-based approaches focusing on specific regions and/or low-frequency (monthly, quarterly, or annual) data. We build on these studies by performing a high-frequency analysis of daily housing returns data from 2nd August, 2007 to 29th November, 2021. We use the *k*-th order nonparametric causality-in-quantiles approach, recently developed by Balcilar et al. (2018). This approach is necessitated by the presence of nonlinearities and structural breaks in our data. It also allows us to test the predictive power of textual-analysis-based daily proxies of physical (natural disasters and global warming) and transition (US climate policy and international summits) climate risks not only on housing returns but also on volatility, for their entire conditional distributions. Our results show that the four factors associated with both types of climate risks predict US housing returns and volatility. Even when considering an alternative dataset of aggregate and regional housing prices, our results hold for both housing returns and volatility.

[7] The data coverage varies across the MSAs as follows: Boston: 5th January, 1995 to 11th October, 2012; Chicago: 3rd September, 1999 to 12th October, 2012; Denver: 5th May, 1999 to 17th October, 2012; Las Vegas: 5th January, 1995 to 17th October, 2012; Los Angeles: 5th January, 1995 to 17th October, 2012; Miami: 3rd April, 1998 to 15th October, 2012; New York: 5th January, 1995 to 23rd October, 2012; San Diego: 4th January, 1996 to 23rd October, 2012; San Francisco: 5th January, 1995 to 18th October, 2012; Washington D.C.: 5th June, 2001 to 23rd October, 2012; and the Aggregate US: 5th June, 2001 to 11th October, 2012.

Given that we study high-frequency data which can be used to infer the future path of economic activity, policymakers, investors, and academics can benefit from the findings of the paper. Policymakers can determine where the housing market is heading due to changes in climate risks. This can be used to infer the future path of economic activity, given that house price movements lead US business cycles. Since we perform daily predictions of housing returns and volatility contingent on physical and transition climate risk, investors can also benefit from our results which can help them make optimal portfolio allocation decisions, involving housing assets among other assets, in a timely manner. Lastly, from an academic perspective, the predictive capacity of climate risks suggests that the housing market is efficient in the semi-strong sense, and more so in the bearish-phase of housing markets.

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Table 1: Linear Granger causality test results

	$\chi^2(p)$	p
US climate policy	6.27	4
International summits	78.00^{***}	8
Global warming	9.40^{*}	5
Natural disasters	5.97	3

Note: *** and * indicate rejection of the null hypothesis of no Granger causality at 1% and 10% levels of significance, respectively, from alternative metrics of climate risks to housing returns, with *p* being the SIC-based optimal lags.

Table 2: Brock et al. (1996) BDS test of nonlinearity

	Dimension (*m*)				
Predictor	2	3	4	5	6
US climate policy	10.49***	10.62***	11.60***	12.11***	12.61***
International summits	15.87***	15.94***	16.32***	16.93***	17.80***
Global warming	12.70***	13.33***	15.23***	16.57***	17.80***
Natural disasters	17.42***	17.88***	18.36***	18.84***	19.49***

Note: 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 housing returns equation with SIC-based lags each of housing returns and a particular climate risk factor; *** indicates rejection of the null hypothesis at a 1% level of significance.

Table 3: *k*-th order causality-in-quantiles test results due to climate risks

Panel A: Housing returns									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	5004.67***	2901.38***	1893.40***	1263.14***	825.12***	506.73***	273.90***	110.53***	14.53***
International summits	5024.20***	2915.23***	1903.47***	1270.41***	830.23***	510.15***	275.99***	111.62***	14.84***
Global warming	5011.33***	2906.47***	1897.19***	1265.88***	827.04***	507.99***	274.64***	110.89***	14.61***
Natural disasters	4987.93***	2891.58***	1886.68***	1258.22***	821.44***	504.00***	271.98***	109.37***	14.15***
Narrative factor	5010.41***	2905.68***	1897.03***	1266.32***	827.93***	509.16***	275.89***	111.97***	15.15***
Panel B: Squared housing returns (volatility)									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3963.90***	2263.76***	1468.06***	977.20***	638.80***	393.82***	214.71***	88.38***	12.76***
International summits	4106.60***	2353.90***	1529.32***	1018.98***	666.39***	410.81***	223.84***	91.99***	13.11***
Global warming	4022.26***	2302.05***	1494.91***	996.12***	651.82***	402.32***	219.74***	90.80***	13.30***
Natural disasters	4120.62***	2365.16***	1536.79***	1023.27***	668.22***	410.85***	222.77***	90.53***	12.27***
Narrative factor	3983.00***	2308.47***	1509.52***	1009.92***	662.27***	409.10***	223.43***	92.41***	13.83***

Note: *** indicates rejection of the null hypothesis of no Granger causality at a 1% level of significance (critical value of 2.575) from alternative metrics of climate risks to housing returns and volatility for a particular quantile.

Table 4(a): *k*-th order causality-in-quantiles test results for housing returns using alternative house price data

Panel A: Boston									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	2.12^{**}	3.40^{***}	3.05^{***}	2.76^{***}	2.31^{**}	2.14^{**}	1.87^{*}	1.51	1.94^{*}
International summits	1.62	2.68^{***}	2.89^{***}	2.68^{***}	2.46^{**}	2.57^{**}	2.35^{**}	1.60	1.75^{*}
Global warming	1.81^{*}	3.33^{***}	2.59^{***}	2.73^{***}	2.91^{***}	2.16^{**}	1.87^{*}	1.74^{*}	1.82^{*}
Natural disasters	1.80^{*}	3.26^{***}	2.62^{***}	2.78^{***}	2.42^{**}	1.91^{*}	1.68^{*}	1.51	1.65^{*}

Panel B: Chicago									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	4.90^{***}	6.24^{***}	3.70^{***}	3.80^{***}	3.40^{***}	2.11^{**}	2.11^{**}	2.97^{***}	3.12^{***}
International summits	4.55^{***}	4.76^{***}	3.16^{***}	2.93^{***}	3.42^{***}	2.48^{**}	2.72^{***}	2.66^{***}	2.26^{**}
Global warming	3.66^{***}	4.51^{***}	2.78^{***}	2.77^{***}	2.72^{***}	1.49	2.14^{**}	2.78^{***}	2.35^{**}
Natural disasters	2.99^{***}	4.66^{***}	3.66^{***}	4.60^{***}	3.80^{***}	1.88^{*}	1.20	1.51	2.23^{**}

Panel C: Denver									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	1.77^{*}	2.04^{**}	3.18^{***}	2.78^{***}	1.84^{*}	1.32	1.39	2.15^{**}	1.25
International summits	1.70^{*}	2.02^{**}	2.41^{**}	2.47^{**}	2.21^{**}	1.45	0.96	2.22^{**}	1.49
Global warming	1.23	1.66^{*}	2.32^{**}	2.43^{**}	1.61	1.81^{*}	2.08^{**}	3.06^{***}	1.37
Natural disasters	1.09	1.23	2.17^{**}	2.55^{**}	1.91^{*}	1.68^{*}	1.84^{*}	3.02^{***}	1.46

Panel D: Los Angeles									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.14^{***}	4.59^{***}	3.59^{***}	2.93^{***}	2.65^{***}	2.22^{**}	2.17^{**}	1.60	1.37
International summits	2.30^{**}	3.93^{***}	3.60^{***}	2.89^{***}	2.25^{**}	2.28^{**}	1.74^{*}	1.51	1.09
Global warming	1.75^{*}	3.47^{***}	3.66^{***}	3.30^{***}	2.25^{**}	2.78^{***}	1.66^{*}	2.05^{**}	1.71^{*}
Natural disasters	1.78^{*}	2.91^{***}	2.60^{***}	1.66^{*}	1.51	1.32	0.99	1.28	1.16

Panel E: Las Vegas									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.53^{***}	6.32^{***}	8.35^{***}	7.10^{***}	6.10^{***}	4.60^{***}	3.73^{***}	2.82^{***}	2.31^{**}
International summits	3.40^{***}	4.83^{***}	6.85^{***}	5.34^{***}	4.35^{***}	4.29^{***}	3.75^{***}	2.89^{***}	2.53^{**}
Global warming	2.85^{***}	4.09^{***}	5.46^{***}	4.36^{***}	3.72^{***}	3.57^{***}	3.46^{***}	3.09^{***}	2.79^{***}
Natural disasters	2.92^{***}	3.55^{***}	4.15^{***}	3.41^{***}	3.31^{***}	3.18^{***}	3.00^{***}	2.40^{**}	2.25^{**}

Panel F: Miami									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	4.51^{***}	7.76^{***}	7.72^{***}	6.88^{***}	4.13^{***}	2.66^{***}	1.68^{*}	2.06^{**}	2.48^{**}
International summits	3.72^{***}	5.61^{***}	4.61^{***}	3.96^{***}	3.17^{***}	2.67^{***}	1.50	1.59	1.49
Global warming	3.85^{***}	5.76^{***}	4.79^{***}	4.43^{***}	3.19^{***}	2.27^{**}	2.29^{**}	2.38^{**}	2.12^{**}

Natural disasters	3.38***	4.84***	4.14***	3.61***	2.03**	1.54	1.45	1.32	1.89*
Panel G: New York									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	1.48	2.01**	3.65***	4.23***	3.07***	3.13***	2.21**	2.53**	1.87*
International summits	1.22	1.36	1.90*	1.39	1.56	1.59	1.56	1.99**	1.47
Global warming	1.23	1.40	1.68*	1.70*	1.55	1.72*	1.66*	1.59	1.52
Natural disasters	1.44	1.33	2.24**	2.35**	2.13**	2.22**	1.95*	1.71*	1.52
Panel H: San Diego									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	1.53	2.86***	2.74***	3.06***	2.33**	1.94*	1.34	1.09	1.22
International summits	1.35	3.17***	2.94***	2.77***	2.46**	1.60	1.33	1.18	1.17
Global warming	1.55	2.88***	2.03**	2.03**	1.74*	1.52	1.43	1.37	1.15
Natural disasters	1.07	2.31**	2.19**	2.61***	2.30**	1.81*	1.26	0.98	0.62
Panel I: San Francisco									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	1.70*	3.06***	3.01***	3.21***	2.62***	2.29**	1.72*	1.43	1.55
International summits	1.59	3.26***	3.01***	2.86***	2.53**	1.82*	1.60	1.46	1.45
Global warming	1.82*	3.16***	2.29**	2.27**	2.11**	1.83*	1.79*	1.66*	1.40
Natural disasters	1.20	2.33**	2.40**	2.69***	2.37**	2.04**	1.48	1.19	0.78
Panel J: Washington D.C.									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	1.41	2.55**	3.37***	3.08***	2.62***	3.30***	3.04***	3.02***	2.06**
International summits	1.17	2.25**	3.13***	2.21**	2.75***	2.46**	2.79***	2.56**	1.92*
Global warming	1.25	2.17**	2.47**	2.68***	2.69***	2.15**	2.73***	2.26**	1.36
Natural disasters	0.75	1.09	1.28	1.48	2.04**	2.00**	2.11**	2.19**	1.55
Panel K: Aggregate									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.27***	4.75***	5.47***	5.73***	4.91***	3.95***	3.29***	2.76***	1.93*
International summits	2.72***	3.53***	4.01***	4.38***	4.18***	3.36***	3.29***	2.87***	2.20**
Global warming	2.35**	4.05***	4.86***	3.33***	2.99***	2.88***	3.03***	2.43**	1.78*
Natural disasters	2.05**	3.32***	3.83***	3.10***	2.64***	2.75***	3.16***	2.50**	2.13**

Note: ***, ** 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 alternative metrics of climate risks to housing returns for a particular quantile.

Table 4(b): *k*-th order causality-in-quantiles test results for squared housing returns (volatility) using alternative house price data

Panel A: Boston									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.67***	5.00***	5.56***	5.74***	6.81***	6.57***	6.59***	5.76***	4.92***
International summits	3.32***	4.37***	5.14***	5.73***	6.98***	6.52***	6.03***	4.80***	3.77***
Global warming	3.27***	4.36***	5.02***	5.24***	5.71***	5.81***	5.37***	4.42***	3.17***
Natural disasters	3.40***	3.81***	4.36***	5.00***	6.42***	5.59***	4.79***	4.49***	3.84***
Panel B: Chicago									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	6.31***	8.77***	10.43***	11.25***	11.59***	11.69***	11.19***	9.30***	7.10***
International summits	5.53***	7.65***	8.88***	9.47***	9.75***	10.14***	9.41***	7.61***	5.96***
Global warming	5.81***	8.15***	9.70***	10.86***	11.71***	11.49***	10.04***	8.39***	6.26***
Natural disasters	5.63***	7.75***	9.15***	9.97***	10.43***	11.30***	10.46***	8.62***	6.30***
Panel C: Denver									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	7.12***	9.82***	11.36***	12.13***	12.55***	11.95***	11.41***	9.78***	6.81***
International summits	6.19***	8.87***	10.38***	10.82***	11.15***	10.98***	10.37***	8.95***	6.55***
Global warming	6.70***	9.20***	11.27***	11.85***	12.08***	11.73***	10.85***	9.16***	6.64***
Natural disasters	6.34***	8.79***	10.99***	11.54***	11.77***	11.35***	10.91***	8.97***	6.29***
Panel D: Los Angeles									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	5.18***	6.76***	7.63***	8.43***	9.09***	8.64***	8.53***	7.40***	5.44***
International summits	4.91***	6.31***	6.91***	8.34***	8.92***	8.49***	7.74***	6.44***	4.79***
Global warming	5.03***	7.05***	7.31***	7.91***	8.43***	7.88***	7.51***	6.05***	4.41***
Natural disasters	3.93***	6.01***	6.51***	7.39***	7.14***	7.02***	6.66***	5.70***	4.22***
Panel E: Las Vegas									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	5.56***	7.69***	9.35***	9.92***	10.77***	10.73***	9.47***	8.27***	6.50***
International summits	5.00***	7.67***	8.36***	9.40***	9.46***	8.67***	8.11***	7.45***	6.16***
Global warming	5.56***	8.36***	8.99***	9.47***	9.71***	9.43***	8.52***	7.60***	5.93***
Natural disasters	4.68***	6.75***	7.59***	8.66***	8.66***	8.33***	7.62***	6.98***	5.52***
Panel F: Miami									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.19***	4.11***	4.53***	6.00***	6.30***	6.42***	6.11***	5.78***	3.82***
International summits	2.85***	3.88***	4.23***	5.18***	4.97***	5.04***	5.20***	4.57***	3.21***
Global warming	3.02***	3.99***	4.61***	5.28***	5.56***	5.48***	5.26***	4.35***	2.85***

Natural disasters	2.57**	2.98***	3.89***	4.90***	4.60***	4.43***	4.58***	3.67***	2.69***
Panel G: New York									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	5.46***	7.67***	9.20***	9.59***	9.96***	9.13***	8.40***	7.22***	5.51***
International summits	4.98***	7.13***	8.04***	8.62***	9.03***	8.81***	8.12***	6.73***	5.19***
Global warming	4.57***	6.73***	7.80***	8.50***	9.47***	7.78***	7.26***	6.12***	4.80***
Natural disasters	4.26***	5.96***	7.15***	7.71***	8.05***	7.61***	7.15***	5.98***	4.63***
Panel H: San Diego									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	2.95***	4.38***	4.36***	5.55***	6.53***	6.51***	6.12***	4.74***	3.81***
International summits	2.80***	4.27***	4.39***	5.17***	6.23***	7.20***	7.14***	4.82***	3.33***
Global warming	2.67***	4.48***	4.11***	4.61***	4.87***	5.11***	5.12***	4.15***	2.80***
Natural disasters	2.15**	3.48***	3.32***	4.29***	4.46***	4.76***	4.63***	3.66***	2.50**
Panel I: San Francisco									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	11.06***	14.69***	16.78***	18.16***	18.37***	17.90***	16.92***	14.63***	10.96***
International summits	10.76***	14.35***	16.44***	17.59***	18.23***	17.68***	16.54***	14.23***	10.62***
Global warming	10.78***	14.50***	16.56***	17.86***	18.37***	17.74***	16.64***	14.37***	10.70***
Natural disasters	10.73***	14.64***	16.70***	17.95***	18.22***	17.60***	16.62***	14.38***	10.77***
Panel J: Washington D.C.									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	5.07***	7.27***	8.56***	8.85***	9.33***	9.50***	9.29***	7.36***	5.94***
International summits	4.58***	6.25***	7.31***	7.84***	7.84***	7.85***	8.23***	6.82***	4.92***
Global warming	4.89***	6.47***	7.65***	8.25***	8.78***	8.61***	8.19***	6.86***	4.96***
Natural disasters	4.35***	5.95***	6.52***	7.40***	7.11***	7.70***	7.55***	5.96***	4.20***
Panel K: Aggregate									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
US climate policy	3.31***	4.58***	5.12***	6.18***	6.22***	6.16***	5.89***	6.32***	4.09***
International summits	3.17***	5.24***	5.41***	5.98***	6.76***	6.78***	6.25***	5.56***	3.48***
Global warming	2.95***	3.99***	4.97***	5.75***	5.56***	5.37***	4.70***	4.48***	3.15***
Natural disasters	3.22***	4.44***	4.44***	5.16***	6.49***	6.27***	5.50***	5.28***	3.41***

Note: *** and ** indicate rejection of the null hypothesis of no Granger causality at 1% and 5% levels of significance (i.e., critical values of 2.575 and 1.96) respectively from alternative metrics of climate risks to squared housing returns, i.e., volatility, for a particular quantile.

APPENDIX:

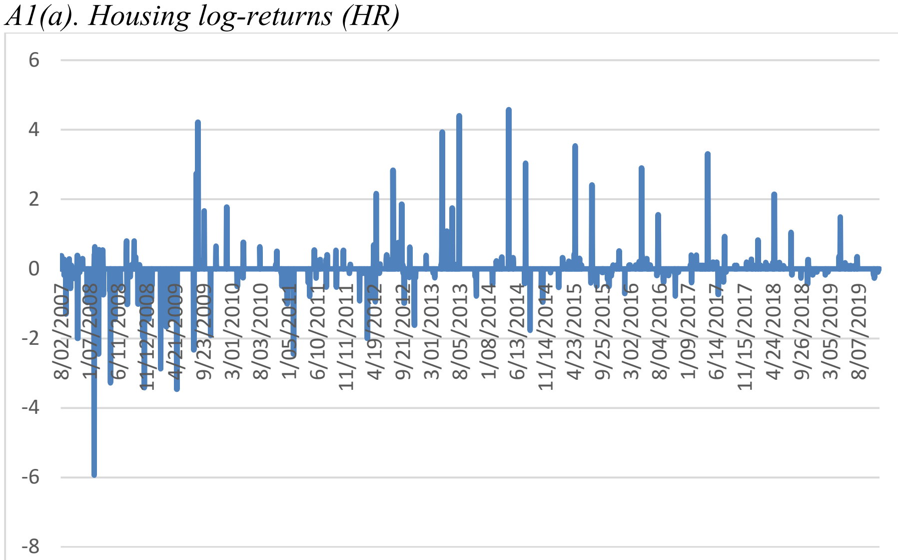
Table A1: Summary statistics

	Variable				
Statistic	Housing log-returns (HR)	US climate policy	International summits	Global warming	Natural disasters
Mean	0.00	0.92	0.45	0.42	0.31
Median	0.00	0.57	0.16	0.21	0.09
Maximum	4.57	10.86	11.96	6.03	4.97
Minimum	-5.93	0.00	0.00	0.00	0.00
Std. Dev.	0.33	1.15	0.72	0.59	0.51
Skewness	0.91	2.39	3.95	2.87	2.95
Kurtosis	114.03	12.01	35.81	16.57	14.70
Jarque-Bera	1595209.00***	13466.13***	147343.70***	28088.55***	22208.45***
ADF	-54.67***	-9.89***	-9.46***	-15.96***	-16.93***
Observations	3105				

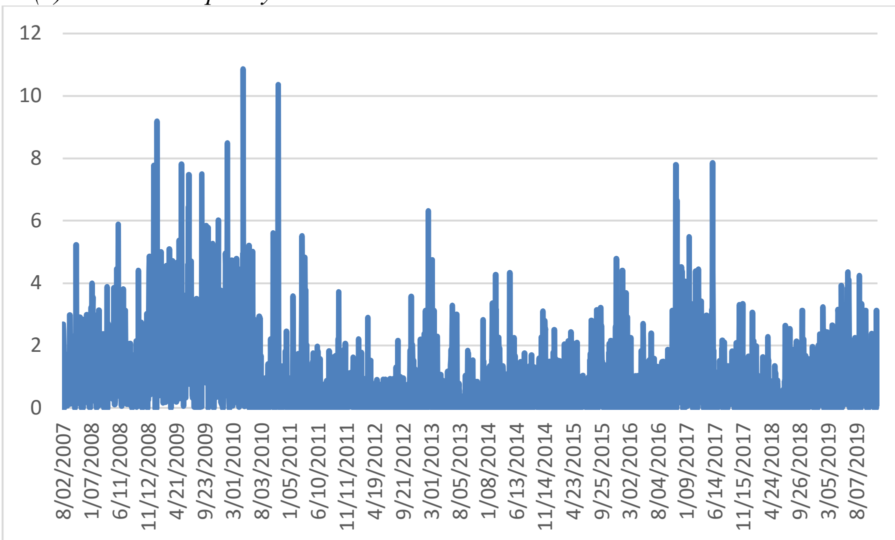
Note: Std. Dev. stands for standard deviation; The null hypotheses of the Jarque-Bera and ADF tests correspond to the null of normality and unit root respectively; *** indicates rejection of the null hypothesis at a 1% level of significance.

Figure A1: Data plots:

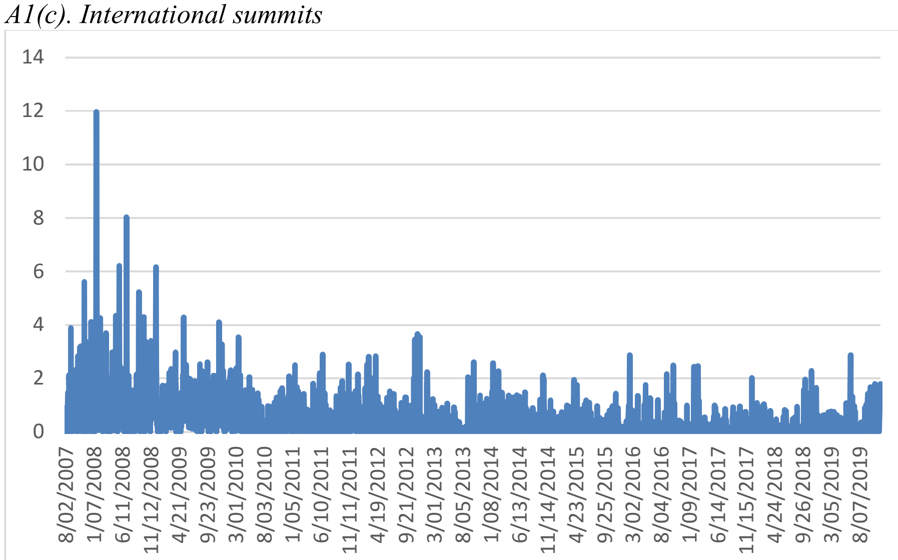
A1(a). Housing log-returns (HR)



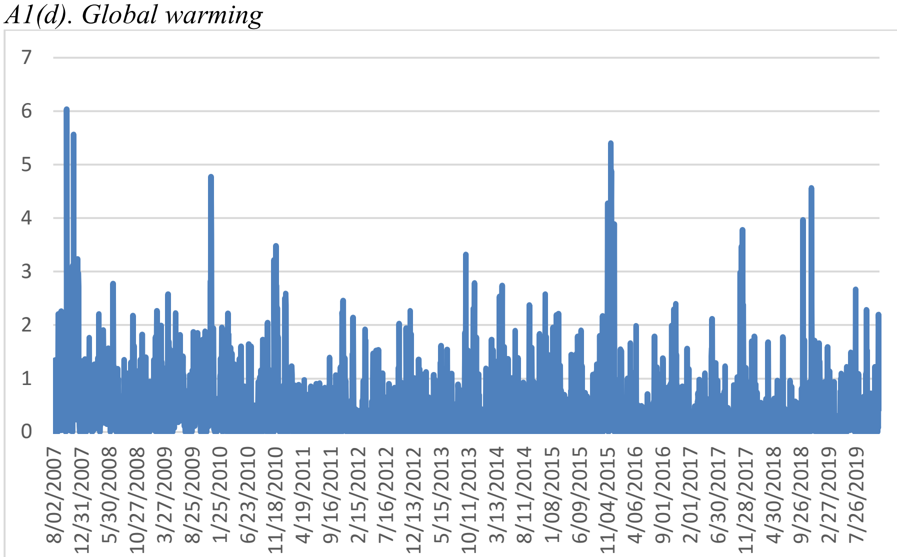
A1(b). US climate policy



A1(c). International summits



A1(d). Global warming



A1(e). Natural disasters