Journal of
Risk and Financial Management

Article

The Role of Political Uncertainty in Climate-Related Disaster Impacts on Financial Markets

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Abstract: This research presents a new model for analyzing the effects of government policies on climatic disasters on financial markets. Using Fama–MacBeth rolling regressions and the construction of model-proposed risk factors, three major risk factors are found to be significant in explaining stock returns. First, there is the risk of climate disasters. Second, there is the risk of uncertainty regarding government actions. Third, there is the risk of government response to climatic disasters. Through the increase in the cost of capital from climate disasters and the uncertainty of government response, the future cost of capital is higher, leading to less investment and lower productivity. However, the government's actions to compensate for losses due to climate damage help offset the damages from disasters. This implies that the previous estimates of economic damages due to climate risk have been underestimated. This work adds to the literature by providing a fuller estimate of the economic implications of climate change.

Keywords: climate risk; political risk; disasters

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Citation: Gregory, Richard Paul. 2024. The Role of Political Uncertainty in Climate-Related Disaster Impacts on Financial Markets. *Journal of Risk and Financial Management* 17: 273. https://doi.org/10.3390/jrfm17070273

Academic Editor: Thanasis Stengos

Received: 16 May 2024
Revised: 21 June 2024
Accepted: 26 June 2024
Published: 29 June 2024

1. Introduction

There has been an increase in both temperatures and CO_2 concentrations on our planet. CO_2 concentrations at Mauna Loa's scientific recording site had climbed to 417.07 ppm in May 2020. The world has not encountered CO_2 levels this high in at least 3 million years (Pagani et al. 2010). Rising CO_2 levels have been shown to cause climatic disasters and rising temperatures. The frequency and intensity of climate disasters have increased as CO_2 levels have risen (see Francis and Vavrus 2012; Lee and Zhang 2012; Rahmstorf and Coumou 2011; Thomas et al. 2014; Thomas and López 2015; Diffenbaugh et al. 2017).

This study provides estimates of the impact of climate disasters on the US economy. The estimates are much larger than Nordhaus (1991), Cline (1992), and Fankhauser (1993). The findings suggest that the ongoing increase in climate-related disasters has resulted in a 6.68% decrease in the US GDP annually on average from 1985 to 2022. However, this has been offset by 4.92% due to government responses to climatic risks. Thus, this work is more in line with the recent work by Keen (2020), which has been critical of the neoclassical work on the economic impact of climate change. It is also in line with Maddison and Rehdanz (2011) in finding a much higher impact of the climate on the economy. This overall decrease in the average GDP growth of 1.76% per year since 1985 may help to explain the productivity paradox that is well documented in the economic literature (Gordon 2013).

Unlike previous research, this work uses a data set that measures a much larger section of the economy and does not assume a fixed relationship between the temperature and GDP. The practical implication of this is that the damages are much larger. Furthermore, this study controls for the response of the government to disasters. And this study also controls for the political uncertainty of government actions. These are important contributions to the literature.

For instance, Nordhaus (1991) only looks at around 13% of the US economy when studying the effects of climate change. He assumes that anything done indoors is not impacted by climate change. Many other studies, as shown by Keen (2020), also follow this assumption. This means that they are not fully capturing the true impact of climate change on the economy by overlooking external factors and supply chain effects.

In a simple illustration, when temperatures rise, there are more droughts. This means less agriculture is produced in the US. Nordhaus and others only consider the economic impacts up to this point. They overlook the fact that the drought will also lead to people turning to foreign agriculture instead of domestic. This will drive up the costs of international trade. Additionally, the drought will slow down demand in the trucking and rail shipping industries, which will result in fewer jobs and lower productivity. It will also cause businesses in the agriculture and shipping sectors to go bankrupt. As a result, banks and insurers will need to raise more money to cover their losses. This will make it harder for other businesses to access capital in the short term. All of these extra effects have been disregarded in the traditional analysis of climate disasters.

This study focuses on publicly traded companies. They represent at least 65% of the US economy (American Immigration Council 2023). Unlike past research, it does not assume that the relationships between climate impacts and the GDP remain constant over time. Instead, it analyzes how the climate affects stock returns. This assumes that the relationship between market returns and the GDP remains consistent in the long term. This approach helps us to better understand the overall economic impact. Previous studies have indicated that stock market returns can provide valuable insights into the economy and any changes taking place within it (Schwert 1989; Campbell et al. 2001).

Secondly, this study controls for the government's reaction to climate impacts on the economy. Previous research has neglected that governments can respond to the occurrence of climate change-related disasters via fiscal policy, emergency relief, and monetary policy (Hein et al. 2019).

Third, it allows for uncertainty in the government's response to climatic disasters. Hausken and Zhuang (2016) show that there can be considerable uncertainty in how the government will respond in terms of fiscal and monetary policies and its future funding of emergency relief. Chebbi et al. (2024) show that more timely government interventions in crises can play a large role in shaping investor sentiment.

The estimates herein show that the government response and the uncertainty of government response save the economy about 4.92% of GDP. While government aid helps, it does not completely offset the effects of climate disasters on the economy due to the uncertainty of the government response.

The overall effect is that there is a 1.76% per annum overall effective risk premium due to climate-related disasters. This may seem modest, but as pointed out by Henry (2003), there is a strong inverse, one-to-one relationship between the market risk premium and real GDP growth rates. Thus, an increase in the risk premium of 1.76% implies an overall decrease in real GDP growth of 1.76% per year. Without this drag on the economy, the real economy would have been nearly twice the size that it was measured to be in 2023!

Also, the overall effect of climate-related disasters could help to explain the "productivity paradox" that has been observed over the past few decades, where digitalization and increased computing power have increased productivity on the micro-level, but do not show up on the macro-level (Hall et al. 2010).

2. Literature Review

Nordhaus (1991), Cline (1992), and Fankhauser (1993) were the first to talk about how the economy would be affected by the rise in CO_2 levels. They predicted that a 3-degree Celsius increase in the temperature could lead to a 1–1.3% drop in the US GDP. Nordhaus also mentioned that the US economy did not have much to do with the climate, with 85% of it not being affected. However, the outlook for the rest of the world was not as positive. Nordhaus predicted that a 3-degree increase by 2090 could result in a 1.8% decrease in world output, with some scenarios showing a 5.5% drop in the GDP.

In 1996, Tol (1996) highlighted how climate change, along with changes in society and the economy, can lead to various losses like immigration, species extinction, and wetland destruction. He also pointed out that the uncertainties related to climate change can lead to additional costs, such as shifting investments from industries with high climate risks to those with lower risks. Based on his previous work, Tol (2002) revised estimates of the world impact of climate change and estimated the median impact to be −2.7% of world GDP from a 1-degree Celsius rise in temperature but emphasized the uncertainty of the estimate.

In a study by Fankhauser and Tol (2005), they looked at how climate change could impact economic growth. They found that climate change could hurt growth both overall and per person by affecting how people save money. Essentially, as the output drops because of climate change, investments will also go down, leading to less production in the future. Their simulations showed that this drop in investment could have a bigger impact, especially for developing nations.

The Stern Review in 2007 (Stern 2007) highlighted the uncertainties in the distribution of future temperature changes and their economic impacts due to climate change. It warned that unless emissions are reduced, there will be significant costs for human development, economies, and the environment. The review also stated that if CO_2 concentrations reach 550 ppm or higher, there will be severe economic consequences, and achieving mitigation with current technology will be extremely challenging for concentrations below 450 ppm.

Pindyck (2009, 2010) shows how climate science and economic impact studies can help guide policy analysis by providing probability distributions for temperature change and economic impacts. Pindyck compares two models for assessing damages: one looks at the direct effects of temperature change on consumption, while the other focuses on the impacts on the growth rate. Using displaced gamma distributions for temperature change and economic impact, Pindyck calculates a metric called "Willingness To Pay" (WTP), which represents the percentage of consumption that individuals would be willing to give up to reduce the negative effects of greenhouse gases. The resulting WTP values are generally lower than the damages estimated by Tol and Nordhaus.

Bansal et al. (2016b) created a long-run risk model that considers how temperature, economic growth, and risk are related. They also factor in the potential impact of global warming by introducing temperature-related natural disasters that can affect both present and future economic growth. Their findings highlight the considerable importance of the social cost of carbon in their model.

Bansal et al. (2016a) discovered that climate change comes with a positive risk premium that goes up as temperatures rise. They also found that this risk premium has nearly doubled in the past 80 years. Additionally, they found that US equity portfolios have a negative relationship with long-term temperature changes.

According to Tol (2018), climate change will not have a big impact on advanced economies in the 21st century. It is the poorer countries and those with lower elevations that will suffer the most. While climate change is expected to affect the global economy and keep more people in poverty, it is hard to measure exactly how much. On the other hand, Hsiang et al. (2017) predicted that the United States will lose 1.2% of their GDP for every 1-degree Celsius increase in the temperature by the end of the 21st century.

Barnett et al. (2019) developed and evaluated a dynamic economic model of climate change, incorporating decision theory, nonlinear response functions, and dynamic valuation through asset pricing. They investigated the uncertainty in how carbon emissions affect temperature changes and demonstrated that the specifics of the economic model can have a significant impact by examining different technological and preference scenarios.

The empirical literature about the effects of climate-related natural disasters on the economy has a rather lengthy lineage. Skidmore and Toya (2002) found that natural disasters weakly promote long-run economic growth, though they also found that natural disasters lead to a loss in physical capital productivity. Hallegatte et al. (2007) found that the GDP exhibits a bifurcation concerning disasters, with GDP decreases being moderate if the intensity and frequency of climate events remain below a threshold value, beyond which the GDP losses increase greatly. Hochrainer (2009), Noy and Nualsri (2011), Raddatz (2009), and Strobl (2011) found that climatic disasters have negative effects on economic growth.

Hsiang and Jina (2014) examined the effects of 6700 tropical cyclones on rich and poor economies and found robust evidence that the GDP declines relative to its pre-disaster trend and does not recover within twenty years! Bourdeau-Brien and Kryzanowski (2017) reported that a small number of climatic catastrophes have an impact on stock returns. The meaningful climatic shocks are found to be confined to firms based in disaster areas and are distributed over a relatively long period.

While Bolton and Kacperczyk (2021) study whether firm carbon emissions affect the cross-section of stock returns, they find that investors charge carbon-emitting businesses a significant premium. However, this neglects the overall effect that carbon has on promoting temperature change and weather.

Lemoine and Traeger (2016) argue that greenhouse gas emissions can trigger irreversible regime shifts in the climate called tipping points. They argue that multiple tipple points affect the probability or each other's occurrence, causing a domino effect. The cost of these tipping points raises the cost of the optimal policy to deal with climate change by mid-century by 150%!

Cai and Lontzek (2019) propose that uncertainty about future economic and climate conditions substantially affects the choice of policies for managing interactions between the climate and the economy. They find the social cost of carbon is a stochastic process with considerable uncertainty and that tipping point elements lead to significant increases in the social cost of carbon.

van der Ploeg and Rezai (2020) argue that there are four risks of asset stranding due to global warming: fossil fuel reserves will be abandoned; fossil fuel exploration assets will be abandoned; unanticipated changes in the present-day or expected climate policies will cause jumps in the current valuations of capital; and, if the intensity and timing of climate policy are uncertain, this will cause a revaluation of assets.

Abbass et al. (2022b) found that climate change is a serious global issue that is affecting various sectors, particularly agriculture, biodiversity, human health, and the tourism industry. It is causing disruptions in weather patterns and temperature ranges, leading to challenges in food production, species survival, disease spread, and economic impacts. Government intervention and strict regulations are necessary to address the impacts of climate change and ensure sustainable development. Countries must work together to mitigate the effects of climate change and protect global sustainability.

Naseer et al. (2023) pointed out that climate change helped to make the COVID-19 pandemic more destructive to the world economy. The pandemic led to a global economic collapse, with many countries implementing lockdown measures that slowed the economic activity and led to job losses. Various industries, including manufacturing, agriculture, education, sports, and entertainment, were negatively affected. Abbass et al. (2022a) provide a Keynesian framework that further illustrates the damages.

Chebbi et al. (2024) investigated the impacts of emergency measures implemented by the US government on the interplay between investor sentiment and the stock performance of financial institutions. By utilizing a novel metric of investor sentiment derived from Twitter data, their analysis reveals that the dynamics of this relationship are intricately linked to the evolving landscape of the COVID-19 crisis and the varied responses of different states within the US. Their findings demonstrate that stringent government interventions during the pandemic had a notable influence on the effect of investor sentiment on the stock returns of financial institutions.

This work develops, in Section 2, a disaster model augmented with a simple interacting environment and a government that seeks to maximize firm dividends payouts through taxation policy. Based on this model, a pricing condition for stock returns is developed that yields premiums in the economy that would affect economic growth: a climatic disaster risk factor, a political uncertainty risk factor, and a political uncertainty risk factor due to climatic disasters. Then, the data are described for the measurement of these factors and the associated control variables. In Section 3, the results are presented, and the chain of causality is first checked between changes in the carbon dioxide levels and damages due to climatic disasters; then, the value of damages due to the risks of climatic disasters, political uncertainty, and political uncertainty due to climatic disasters is estimated. Section 4 provides a discussion. Section 5 concludes this article.

3. Methodology

3.1. The Data

The choice of the data used is dictated by availability, the model described in Section 3.2, the appendices, and the asset pricing literature in financial economics.

To measure the disaster shock θ_t, this work uses data on the United States from January 1985 through December 2022. To tabulate the deaths and damage associated with climate-generated events, this research begins with the events listed in the Storm Events Database (SED) maintained by the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration (NOAA) (accessed on 4 April 2023). Only events for which deaths and/or damage estimates are available are included. The time frame ranges from January 1985 through December 2020 due to data availability. From 1955 through 1996, only tornado, thunderstorm, wind, and hail events were entered into the database. From 1996 on, over 48 types of atmospheric events were entered into the database. Details of the data preparation can be found at https://www.nws.noaa.gov/directives/sym/pd01016005curr.pdf (accessed on 4 April 2023).

To make the coverage of events more comprehensive over the sample period, the SED has been supplemented with several additional sources. From 1985 to 1996, the monthly "Storm Data" (SD) publication from the National Climatic Data Center (NCDC) was used. The SD contains a chronological listing of storm occurrences and unusual weather phenomena. The reports contain information on deaths, injuries, and property damage. From 1996 onwards, damages are categorized into ordinal categories. In each case, the mid-point of the category is used to estimate damages, unless additional information was provided. To supplement the coverage of floods, the "Summary of Significant Floods in the United States, Puerto Rico, and the Virgin Islands, 1970 Through 1989" was consulted.

Events were also checked against the EMDAT database (EM-DAT: The Emergency Events Database, Université Catholique de Louvain (UCLouvain), CRED, D. Guha-Sapir, www.emdat.be accessed on 15 May 2024, Brussels, Belgium). Great care was taken not to count events, damages, and deaths twice. Where conflicting information on the same climatic event was available, the lower estimates of direct deaths and damages were used. Where climatic events took place over more than one month, the deaths and damages were apportioned by the weighted average number of days the event took place per month, unless the information was available to allow for the apportioning of deaths and damages to specific dates.

After summing the data over the individual months, the economic value of lives lost was determined by multiplying the number of lives lost during the month by the economic value of life determined by Viscusi and Aldy (2003), adjusted annually by changes in the value of the GDP. Adjustments to damages for injuries were not made for two reasons: (1) injuries are recorded in a very inconsistent manner in the records provided by NOAA, with many records recording injuries as "few" or "several"; (2) there are no studies on the economic cost of climatic disaster-related injury costs. Thus, I accept that the figures that I provide here necessarily underestimate the true economic costs of climatic disasters.

Also, it should be noted that damages are sometimes recorded in the records in a categorical fashion, where, for instance, a "4" indicates damages were from USD 5000 to USD 50,000. I recorded such data as the median (USD 27,500) unless actual figures were given. The monthly data are divided by the annual GDP.

The measure of policy uncertainty σ_c^2 is the first difference of the economic policy uncertainty index constructed by Baker et al. (2016), available at https://www.policyuncertainty.

com/us_monthly.html (Accessed 12 April 2023). The overall index is used. The measure of the combined policy uncertainty and climate damage, $\theta_t\sigma_c^2$, is the multiplicative sum of the economic damage variable and the first difference of the economic policy uncertainty index.

As control variables, the Fama–French factors are used (Fama and French 2017) as well as a dummy variable for the months of the COVID-19 pandemic, as determined by the Center for Disease Control (https://www.cdc.gov/museum/timeline/covid19.html) (accessed on 12 April 2023).

3.2. The Model

The standard, real business cycle model used includes a representative household and multiple goods producers. There is a monetary authority that sets the nominal interest rate based on a Taylor Rule. For more information, refer to Appendices A and B for the detailed model.

The new model considers a rare disaster shock that changes over time and depends, in part, on CO_2 levels. It shows how climate disasters can have long-lasting effects on the economy, including lower productivity, decreased values of assets, and reduced household budgets. Right after a disaster, there is an immediate drop in the values of technology and assets and in household budgets. These shocks have both a predictable random part and an uncertain aspect that becomes more important as carbon dioxide levels rise. People can choose to sacrifice future consumption and invest to improve technology, assets, and household budgets in the future, but this decision will require adjustments to their investment plans, ultimately affecting the cost of investments and future returns. Climate shocks also affect firms by destroying capital, driving up the cost of factors such as labor and causing a future decline in the path of the technology level. This will affect the future demand for capital and returns to financial assets.

The government's decision-making process is similar to Pastor and Veronesi's model but differs in that it lacks current information on household wealth. Instead, it focuses on real-time data on changes in average firm profitability, such as earnings announcements and stock market trends. As a result, the government aims to adjust its policies to maximize the impact on average firm profitability, which is seen as a proxy for investor wealth.

As a result, government economic policy is pro-business and responsive to circumstances. The budget is subject to limits. Two types of risks result from these conditions: first, the uncertainty that accompanies the political regime in power, or political risk; and second, the political risk that accompanies disasters. This risk comes from whether the government will respond to the tragedy and how much.

From Appendix B, the return on a stock is:

$$\begin{gathered}\widetilde{q}_t^e = E_t\left(M_{t+1}\left(\widetilde{div_{t+1}} + +\widetilde{q_{t+1}^e}\right)\right) = \\ \mathrm{E_t}(\beta_0[\mathrm{E}\left[1-\mathrm{p_{d,t}}+\mathrm{p_{d,t}}\exp((1-\gamma)\ln(1-\theta_t))\right]^{\frac{1-\psi}{1-\gamma}}\frac{\lambda_{t+1}}{\lambda_t}(\widehat{z}_t)^{-\psi}\mathrm{B})(\mathrm{p_t}\widetilde{\mathrm{y}}_{i,t}+ \\ t_t(\sigma_c^2,\theta_t) - \widetilde{w_{i,t}}l_{i,t} - \widetilde{x_{i,t}} - n_{i,t}e_{i,t} - \varphi\theta_t) + \widetilde{q_{t+1}^e}\end{gathered} \tag{1}$$

Stock returns are directly affected by θ_t, the size of the disaster shock. They are also influenced by the size of the lump sum payment of the government to firms t_t. This will be influenced by the size of the disaster shock and the uncertainty of the government policy response. Thus, there are three factors of uncertainty in the model: first, the disaster shock, θ_t; second, the government's uncertainty response, σ_c^2.; and third, the combined government uncertainty response and disaster shock, $\theta_t\sigma_c^2$. Equation (1) shows that under the model assumptions, these risks will be priced.

To simplify the model's implications, the following diagram may be useful:

Figure 1 essentially shows that increased economic activity leads to higher carbon dioxide levels, which increase temperatures and lead to more water vapor. This, in turn, leads to more frequent and more destructive climatic disasters. As a result, firms and households are more likely to hold onto cash and make less long-term productive investments that lead to greater productivity. This, in turn, makes the risk premium of long-term investments like stocks higher. This rise in the risk premium can be offset by government actions to tax/borrow funds in order to act as a guarantor to make good the cost of disasters. But if the government faces a budget constraint, then this adds a third source of risk related to whether the government will be able to fully guarantee the losses due to disasters.

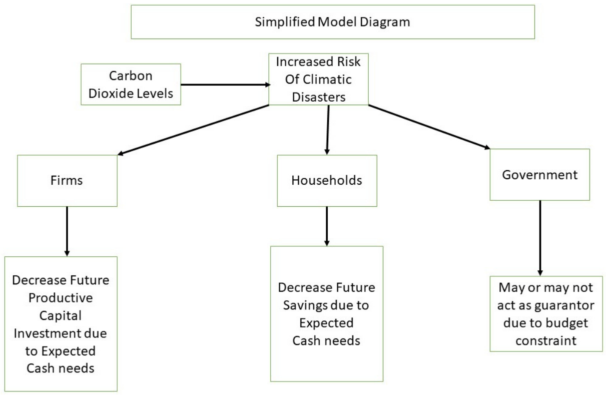

Figure 1. Simple Illustration of the model in Appendices A and B.

4. Results

4.1. Descriptive Statistics of the Predictive Variables

Table 1 exhibits the descriptive statistics for the predictive variables EV (the economic value of losses due to climatic disasters), PO (the change in the economic policy uncertainty variable), MKT (the Fama–French market factor), HML (the Fama–French High-Minus-Low Factor), SMB (the Fama–French Small-Minus-Big Factor), CMA (the Fama–French Conservative-Minus-Aggressive Factor), and RMW (the Fama–French Robust-Minus-Weak Factor). Also exhibited are the unit root test results for the variables. For the economic damages, the ADF and Phillips–Perron (PP) tests reject the null hypothesis of the series having a unit root. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, where the null hypothesis is that the series is stationary, fails to reject the null, so it is concluded that the economic damage series is stationary.

4.2. The Overall Effects of Climatic Disasters and Government Responses to Disasters

To measure the overall effects of climatic disasters, the risk premiums of θ_t, the economic value of climatic disasters (measured by EV), σ_c^2, political uncertainty (measured by PO, the first difference of the economic policy uncertainty index constructed by Baker et al. 2016), and $\theta_t\sigma_c^2$, political uncertainty due to climatic disasters (which is measured by EP = EV × PO), are estimated.

To control for other sources of risk, the French–Fama (Fama and French 2017) five-factor model is used. To estimate the risk premiums, the Fama–MacBeth approach is used with a portfolio of returns from 30 US industries. It should be noted that by using industry portfolios, the tests of running Fama–MacBeth regressions are biased against finding results in favor of finding an effect for EV, in that it is expected that most firms would have hedged against climate damage by taking out insurance and/or purchasing climate derivatives (see Smith and Katz 2013). This would lead to insignificant factor loadings and presumably an insignificant risk premium. If investors invest in insurance companies that write policies for climate-based claims and investors take the opposite sides of climate derivate contracts, then, the variable EV may still be priced. Similar holds true for PO and EP, but for differing reasons, in that investors can hedge against their exposure to these variables through political donations and other means of political influence.

As noted in the literature, the two-pass rolling Fama–Macbeth method of estimating risk premiums has weaknesses due to endogeneity issues in using the first-pass estimates in the second-pass estimation. Kan and Zhang (1999) found that useless factors are often priced by the estimator when they should not be. Anatolyev and Mikusheva (2022) note that the exclusion of non-included factors can exacerbate this problem due to cross-sectional dependence in the error terms of the second-pass regression.

Table 1. Descriptive statistics of exogenous variables. This table exhibits the descriptive statistics and unit root test statistics of EV, PO (the change in the economic policy uncertainty index), MKT_t, which is the market factor, HML_t (High Minus Low: the average return on the two value portfolios minus the average return on the two growth portfolios), SMB_t (Small Minus Big: the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios), CMA_t (Conservative Minus Aggressive: the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios), and RMW_t (Robust Minus Weak), which is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. ADF is the augmented Dickey–Fuller unit root test and PP is the Phillips–Perron unit root test, both in which the null hypothesis is that the tested series has a unit root. KPSS is the Kwiatkowski–Phillips–Schmidt–Shin test, where the null hypothesis is that the series is stationary. * signifies significance at the 5% level or less.

Series	**EV**	**PO**	**MKT**	**HML**	**SMB**	**CMA**	**RMW**
Mean	0.003	−0.002	0.571	0.153	0.325	0.305	0.344
S.D.	0.009	0.741	4.624	3.025	3.077	2.287	2.058
Skew.	10.12	0.475	−0.513	0.375	0.114	−0.291	0.362
Kurt.	128.26	2.518	4.675	6.432	5.131	14.03	4.373
ADF	−18.03 *	−22.54 *	−24.05 *	−24.15 *	−21.13 *	−21.32 *	−21.35 *
PP	−18.03 *	−22.31 *	−24.04 *	−24.16 *	−21.32 *	−21.22 *	−21.44
KPSS	0.043	0.15	0.13	0.09	0.27	0.15	0.19
Pearson correlation							
EV	1.000						
PO	−0.062	1.000					
MKT	0.03	0.15	1.000				
HML	0.01	0.04	0.26	1.000			
SMB	0.12	0.18	−0.22	−0.03	1.000		
CMA	−0.06	−0.05	−0.19	−0.37	0.13	1.000	
RMW	0.03	−0.03	−0.37	−0.07	0.69	0.04	1.000

To help guard against accepting weak or useless factors, the Shanken (1992) errors in variable robust t-statistics and the mis-specification robust t-statistics of Shanken and Zhou (2007) are calculated. The bootstrap t-statistics are from a wild bootstrapped re-sampling of the variables over 10,000 replications. In addition, I performed the equally weighted scaled median test proposed by Harvey and Liu (2021) on the first-stage estimated intercepts to test the individual factors. These would not be subject to any endogeneity problems.

The model estimated is:

$$\mathrm{E}(\mathrm{r_i}) = \alpha_{\mathrm{i,l}} + \sum_{\mathrm{l=1}}^{\mathrm{L}} \beta_{\mathrm{i,l}}\gamma_{\mathrm{l}} \tag{2}$$

where γ_l are the slope estimates on the individual factors from a first-stage regression on the returns of the portfolios of 30 industries. I include a dummy variable for the periods in the US when the COVID-19 pandemic occurred, as suggested by an anonymous reviewer. $E(r_i)$ are the monthly individual portfolio returns, and $\alpha_{i,l}$ is the estimated return on the zero-beta portfolio. $\beta_{i,l}$ are the estimated monthly risk premiums.

Table 2 exhibits the results of estimating the Fama–Macbeth regressions outlined above.

MKT_t is the market factor, HML_t (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, SMB_t (Small Minus Big) is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios, CMA_t (Conservative Minus Aggressive) is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, and RMW_t (Robust Minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. The data on the risk factors and the industry portfolio returns are all from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed on 14 April 2023).

Table 2. Fama–MacBeth rolling regressions estimation: time-series and cross-sectional summary statistics for 30 US industry-sorted portfolios from a Fama and MacBeth (1973) regression. Panel A provides the average absolute intercept value (Alpha), the average adjusted R^2 (AAR^2), and the GRS F-test statistic (GRS F-test). Panel B contains the cross-sectional regression results, reporting the estimated risk premium for each factor. t-EIV values are the Shanken (1992) errors in variable robust t-statistics. t-MIS values are the mis-specification robust t-statistics of Shanken and Zhou (2007). The bootstrap t-statistics are from a wild bootstrapped re-sampling of the variables over 10,000 replications. R^2 is the ordinary least squares adjusted R^2.

Panel A Time-Series Statistics 1985:01–2022:12					
		GRS F-test prob.	**Alpha**	**AAR^2**	
Five-factor model		0.0095	0.157142	0.6221	
Panel A cross-sectional statistics					
		Coeff.	t-EIV	t-MIS	Bootstrapped t-statistic
Five-factor model	Constant	0.2876	1.3039	1.1419	1.2711
	MKT	0.8030	4.1820	2.0450	4.4212
	HML	0.5562	2.8419	1.6858	2.8448
	SMB	0.0586	0.5332	0.7302	0.6050
	CMA	0.1284	0.7675	0.8761	0.7228
	RMW	0.3104	2.1564	1.4685	2.2656
	R^2	0.5169			
Panel B Time-series statistics 1985:01–2022:12					
		GRS F-test prob.	**Alpha**	**AAR^2**	
Five-factor model plus EV, PO, and EP		0.2929	0.1039	0.6223	
Panel B cross-sectional statistics					
		Coeff.	t-EIV	t-MIS	Bootstrapped t-statistic
Five-factor model plus EV, PO, and EP	Constant	0.0583	1.5982	1.5556	2.3734
	MKT	1.1381	135.3804	12.7699	84.1015
	HML	0.7411	66.1156	9.9521	17.7824
	SMB	0.3000	31.3597	6.7975	30.0124
	CMA	0.1444	12.9842	5.1936	29.3854
	RMW	0.3109	40.7221	7.4781	47.2557
	EV	0.4471	124.3552	11.7553	93.7345
	PO	0.1097	47.2297	7.0865	18.0797
	EP	−0.1125	4.5127	2.5880	5.2448
	COVID-19 period	−0.0145	1.2357	1.5421	1.3487
	R^2	0.9995			

For comparison purposes, the first estimate uses the Fama–French five-factor model over the sample period. The time-series and cross-sectional results for the five-factor model are shown in Panel A. The results for the model outlined above are shown in Panel B. The GRS F-test has the null hypothesis that the $\alpha_{i,I} = 0$. The test rejects the null at the 1%

level. This means that the model has been estimated so that the zero-beta (no risk) portfolio has a premium not equal to zero, meaning that holders of a risk-free portfolio can earn a guaranteed positive profit, which would violate the hypothesis of weak market efficiency.

As can be seen, the null of the GRS test for conventional levels of significance cannot be rejected for the model with the climate disaster risk factor, the political risk factor, and the political risk due to climate disasters factor. The null hypotheses that these factors are equal to zero are uniformly rejected. The average alpha is also lower, and the average R^2 is higher for the augmented model. Taken together, these statistics indicate that the augmented model fits the data better than the standard five-factor model.

Looking at the coefficients, the coefficient on EV is positive and significant based on the Shanken (1992) errors in variable robust t-statistics, the mis-specification robust t-statistics of Shanken and Zhou (2007), and the bootstrapped t-statistics. The risk coefficients on PO and EP are also both positive and significant for all the t-statistics. Surprisingly, the coefficient on EP is larger than the coefficient on PO, indicating that the coefficient on political uncertainty due to climatic disasters may lead to a higher risk premium than that which is due to "normal" political uncertainty. A possible explanation for this is concerns about debt ceilings, which, in the United States, are binding and can create uncertainty about the amounts and timing of relief for damages to climatic disasters.

To test for endogeneity in the second stage estimation, I use the Guo et al. (2018) Q-test, which has been shown to have better power in detecting endogeneity than the standard Durbin–Wu–Hausmantes test (Durbin 1954; Hausman 1978; Wu 1973).

The Q-tests in Table 3 indicate that there are no endogenous variables in the estimation of the second-stage regression.

Table 3. Tests for endogeneity. The table reports the results of testing the second-stage regression variables from the five-factor plus EV, PO, and EP model in Table 4 using the Guo et al. (2018) Q-test for endogeneity. The null hypothesis has no endogeneity, and rejection of the null at the 5% level or less indicates the variable is endogenous.

Variable	Q-Test Prob.
Constant	0.2961
MKT	0.5723
HML	0.8099
SMB	0.5261
CMA	0.3953
RMW	0.3649
EV	0.4278
PO	0.5486
EP	0.6909
COVID-19 period	0.8997

Table 4 gives the first-pass estimates of the individual industry exposures to the climate-related factors and the political risk factor. Simply put, the results in Table 4 show which industries are significantly exposed to the three new factors.

The agriculture- and construction-related industries uniformly exhibit significant exposures to the climatic disaster risk factor, EV, as do natural resource-dependent industries such as mining. Also, the retail industry shows a significant exposure. For the factor regarding uncertainty due to the government's response to climate-related disasters, EP, many of the same industries have significant exposures. This is similar to the results of Nordhaus (1991); however, the inclusion of industries like retail, chemicals, etc., makes the results far more reaching and illustrates the importance of supply chains in determining the effects of climate on the economy. Even though retail and chemical workers and businesses are assumed, in previous studies, to be insulated from climate-related disasters, the effects of disasters on their inputs from raw materials and transportation leave them effected significantly.

Table 4. Industry factor loadings. Table 4 reports the 30 industry factor loadings for the EV, PO, and EP factors estimated from the first-pass regressions and the R2. To save space, the associated Newey–West HAC robust t-statistics are not reported. The 10% or less significant factor loadings are in bold.

Industry Portfolios				
	EV	**PO**	**EP**	**R^2**
Food	**194.4483**	0.3048	**−2784.7120**	0.5807
Beer	**510.2812**	−0.3776	**−4896.7774**	0.4617
Smoke	**210.2350**	1.1321	**−3757.4038**	0.2904
Games	−356.7717	0.3833	−5107.4403	0.6808
Books	−133.3991	0.4015	−4341.5073	0.7290
Hshld	**291.5629**	**−1.9117**	4277.3125	0.5861
Clths	**62.7707**	**−2.5841**	5477.8627	0.6439
Hlth	**38.4567**	1.6403	91.6652	0.6072
Chems	**−607.6523**	−1.1363	**−6672.3194**	0.7221
Txtls	**−75.5897**	**−3.5769**	**−303.7589**	0.6037
Cnstr	**6.5522**	0.0749	**−3944.4410**	0.7937
Steel	**−619.3367**	**2.6705**	**−10,149.99**	0.6669
FabPr	**−290.1879**	−0.9376	**−7341.7030**	0.7706
ElcEq	40.8919	−1.4095	−2260.0934	0.7454
Autos	11.6072	**−4.3480**	2576.3800	0.6464
Carry	**−168.2385**	−1.7186	**−3543.5347**	0.6373
Mines	**−208.2524**	**3.1896**	**−7794.3733**	0.2580
Coal	**−139.4499**	**3.1656**	**−20,607.592**	0.2047
Oil	**168.1259**	−0.0473	**−3157.8725**	0.4282
Util	**69.9277**	1.0616	**−2072.5470**	0.3259
Telcm	−95.7988	1.7166	**−1051.6758**	0.6674
Servs	151.5409	−0.4251	2972.2134	0.8689
BusEq	−62.9400	**−2.5099**	3178.6267	0.7876
Paper	−53.0622	−1.1406	525.9809	0.7323
Trans	**−92.7953**	−0.6041	**−2294.6479**	0.7041
Whlsl	−195.8313	1.0899	**−4247.6199**	0.7867
Rtail	**−213.9851**	0.4842	22.2286	0.7121
Meals	51.5646	−1.0272	3727.6229	0.6355
Fin	68.9157	0.4696	436.4539	0.8656
Other	−3.0154	1.1113	−421.7409	0.6565

Table 5 gives the estimates of the annual impact on the cost of equity. To determine the average earned risk premium from the significant factors, I multiplied the market-weighted industry factor loadings from Table 4 by the estimated factor premium in Table 2 and summed these over the industries. The estimated average risk premium due to climatic disasters (EV) is 6.68%. The estimated average risk premium of political uncertainty due to climatic disasters (EP) is −4.92%; it would normally be expected to be negative if the government was expected to act as a guarantor to losses to climatic disasters, as this would be compensation to firms and investors for losses. The estimated average risk premium of other sources of political uncertainty (PO) is 1.1%; however, the associated t-test does not exclude the possibility that the average risk premium could be zero. Therefore, the total market impact of climate-related disasters is estimated by this model to be 1.76% per year on average (6.68–4.92%).

Table 5. The average risk premium impact of the economic value of climatic disasters and combined climatic disasters and political uncertainty on US industries. The average risk premium from the economic value of climatic disasters on the cost of equity is measured by multiplying the weighted average loading of the factor by the estimated factor risk premium times the mean value of the economic impact in Table 1, similar to the combined climatic disaster times the political uncertainty factor (EP) and political uncertainty factor (PO). The t-ratios are calculated using the industry market-weighted average standard errors of the estimates. Significance at the 5% or less level is signified by *.

Average Risk Premiums of Climatic Disasters and Combined Climatic Disasters and Political Uncertainty	
Average risk premium of EV, climatic disasters	6.68%
t-ratio: H_0/risk premium = 0	34.0152 *
Average risk premium of EP, political risk due to climatic disasters	−4.92%
t-ratio: H_0/risk premium = 0	22.9453 *
Average risk premium of PO, political risk	1.1%
t-ratio: H0/risk premium = 0	0.7912

As a test of the robustness of the significance of the estimated risk premiums on EV, EP, and PO, I use the equally weighted scaled median test proposed by Harvey and Liu (2021):

$$SI_{ew}^{m} = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(\left|a_i^*\right| - \left|a_i\right|\right)/S_i}{\frac{1}{N}\sum_{i=1}^{N}\left(\left|a_i\right|\right)/S_i} \quad (3)$$

where $|a_i|$ and $\left|a_i^*\right|$ are the absolute values of the median of the cross-sectional regression intercepts for the baseline model and the augmented model, respectively, and S_i is the cross-sectional standard error for regression intercepts under the baseline model. I use bootstrap statistics to find 5% probability limits and to estimate the probability of test statistics using 10,000 random draws from the data. The advantage of the Harvey–Liu test on the individual factors is that it does not rely on the estimated covariance matrix to test the significance of the coefficients, but rather on the median cross-sectional intercepts of the model, thus minimizing the effects of endogeneity.

The results are presented below in Table 6.

Table 6. Harvey–Liu tests on factors. This table displays the results of the risk factors EV, EP, and PO. The baseline model is the model that includes no risk factors. The metric $\mathrm{SI}_{\mathrm{ew}}^{\mathrm{m}}$ measures the difference in the equally weighted scaled mean absolute regression intercept. The 5th percentile and *p*-value for multiple tests are the multiple-testing-adjusted 5th percentile and *p*-value, respectively.

	Baseline = No Factors			**Baseline = Five Factors**		
	$\mathbf{SI^{m}}_{\mathbf{ew}}$	**5th Percentile**	***p*-Value**	$\mathbf{SI^{m}}_{\mathbf{ew}}$	**5th Percentile**	***p*-Value**
EV	−0.9529	−0.1899	0.0004	−0.976	−0.1805	1.428×10^{-5}
EP	−0.2799	−0.1637	4.258×10^{-5}	−0.3412	−0.2655	0.0852
PO	−0.1004	−0.1258	0.1473	−0.1147	−0.1584	0.0174

As can be seen, the EV and EP factors are significant in reducing the size of the individual first-stage intercepts compared to the model with no other factors and compared to the model with the five factors. The PO factor is significant versus the five-factor but not the no-factor model, which again brings into question if the generic political risk is being priced based on an average. This means that the climate disaster risk factor and the political risk due to climate disaster factors help to explain systematic risk premiums amongst the portfolios assuming both a five-factor model and no-factor model. This shows that they are likely significantly priced factors in determining stock returns.

Overall, the estimated effect of climate disasters is an increase in the risk premium of 1.76% per year. This means that market conditions were such that on average, companies had to invest to earn an extra 1.76% per year due to climate disasters over the sample period.

5. Discussion

Using a disaster model, conditions for determining how economic damages from climatic disasters will affect market returns alone and in combination with political uncertainty due to climatic disasters are derived. Climate disasters cause economic damage by creating uncertainty in future consumption, production, and government responses to climate disasters.

Empirical work from 1985 shows that climatic disasters, as specified in the model, are Granger-caused by changes in the carbon dioxide level, even when controlling for other factors. Empirical work also shows that the risk from climatic disasters and risk from political uncertainty due to climatic disasters are priced in the stock markets, earning a premium of 6.68% and −4.92%, respectively. As demonstrated through several tests, the results are very robust given the assumptions.

The risk premium of 6.68% per year arises from households demanding a larger risk premium for making long-term investments like stocks, when, to face cash needs due to disasters, they prefer to hold more cash than they would otherwise. It also comes from firms underinvesting in long-term assets due to the need for cash to buffer against disasters, thus lowering overall productivity.

The effect of climate-related disasters on the market to raise the risk premium by 6.68%, according to the work of Henry (2003), implies that with an inverse one-to-one relationship between a change in the market risk premium and real GDP growth, the economic effect of climate-related disasters due to climate change is to lower potential GDP growth by 6.68%. This is a much larger impact than estimated by Nordhaus (1991), Cline (1992), and Fankhauser (1993). The big difference here is that I included a much wider range of industries than they did to measure the economic effects, recognizing that difficulties in one industry can affect the entire supply chain.

The −4.92% risk premium from political uncertainty due to climatic disasters arises due to the US Federal Government budgetary process, where there are budget constraints, so there is uncertainty over whether the government will fully guarantee losses due to climatic disasters. On the other hand, the negative sign of the average risk premium shows that on average, the market expects that ultimately the government will act as a guarantor to climate disaster-related losses much of the time.

Given the work by Henry (2003), that the risk premium rises one by one with expected GDP growth, this implies that the climatic disaster risk decreases growth by 6.68% per year in the United States, well above previous estimates by Nordhaus (1991), Cline (1992), and Fankhauser (1993), who generally found estimates in the range of 1–1.3%, though it is not as high as the estimate of Maddison and Rehdanz (2011). Thus, this work is more in line with recent work by Keen (2020), which has been critical of neoclassical work on the economic impact of climate change.

However, this is offset by the government's responses to the climate-related disasters. As estimated, the risk premium associated with the uncertainty of the government response to climate-related disasters is −4.92% per year. Thus, the total effect felt by the economy, on average, is a decrease in growth by 1.76% per year.

Henry (2003) found that real GDP growth varies inversely with the market risk premium, one for one. Given the real GDP in 1985 was USD 8.8 trillion in 2017, then this means that real GDP in 2023 would have been USD 42.95 trillion in 2023, USD 20.55 trillion more than it was in 2023 (USD 22.4 trillion) if it had not been for the climate-related disaster risks and the uncertainty of the government response to them. This means that average real GDP growth throughout 1985–2022 would have averaged 4.26% instead of 2.5%. For the previous 36 years, 1949–1985, the real GDP growth was 3.6%. It should be noted that the difference in the average real GDP growth between the eras (1.1% per year) is of similar size to the estimated effect of climate-related disasters via the risk premiums (1.76%).

Thus, it may be that the increase in climate-related disasters can help explain the productivity paradox that has been associated with the increase in technology. The improvements in technology are documented to be increasing the productivity on the micro-level (see Hall et al. (2010) amongst many). This may be, in part, offset by the rising frequency and intensity of climate-related disasters.

6. Conclusions

This study investigates how economic damages caused by climatic disasters affect market returns. An analysis of the US reveals that variations in the carbon dioxide levels are a large factor in explaining climatic economic damage. The study also discovers that the risks linked with climatic disasters have a premium of 6.8% per year. The risk premium of the political uncertainty of the government's responses is -4.9% per year. According to earlier research, climate disaster risk affects the annual GDP growth in the United States by 6.8% per year, which is greater than previously estimated.

The model could be enhanced by integrating a more complete depiction of government policy, such as accounting for government debt and tax policies. This would make the model more realistic and reflect the impact of uncertainty on future economic growth. Adding complexity through interaction with other variables would also improve realism. When comparing this study to earlier studies on the effects of climate change on the economy, it is crucial to highlight that this study takes a broader view of the economy and does not assume a continuous relationship between GDP and temperature change, as previous research has done.

This study finds that climate-related disasters have a significant effect on the economy and financial market, which is only partially counteracted by government interventions. Despite the current relatively small increase in the temperature caused by greenhouse gases, the impact on the market may be exaggerated. Further research is needed to explore this possibility.

The research findings have important implications for policymakers, as they can use this information to better understand how government actions affect financial institutions and stock market outcomes. Policymakers can customize their interventions to achieve desired economic and financial results, especially during times of crisis, by implementing strategies that promote positive market sentiment and support financial institutions. Policymakers must consider the complex relationship between government actions, market sentiment, and financial institution performance when creating policy measures. For investors and investment analysts, this research makes clear that climate change is a major source of risk that has been compensated by the government's guarantee to pay for climate damages. This should be weighed carefully in making political decisions and in making investments.

Of course, there may be other offsetting risks and effects that are unaccounted for here. For example, Racherla and Adams (2006) note that some types of emissions, some particulate matter, and ozone depletion from water vapor that arises from human ozone production may help offset some of the climate changes due to rising greenhouse gas levels. But then, increased particulate matter and ozone depletion also have other risks of their own.

In the proposed model, climate-related economic disasters affect the economy through several different channels. This paper only measures the direct effects on household portfolio holdings, their consumption preferences, and firm demands for capital based on future demands for capital. It does not account for the effects of household savings, which may help alleviate the effects of climate-related disasters.

Also, the model follows a simple Taylor Rule in setting monetary policy. This ignores that the monetary authority, during times of disasters, may come under pressure to temporarily abandon a strict Taylor Rule. This source of risk is unaccounted for and is left to future research.

Furthermore, the model makes the restrictive assumption that government fiscal policy solely responds to the needs of firms. In times of disaster, if the disaster is big enough, the government may also respond to the needs of households. Again, this is left to future research.

For investors, the implications are that climate change and the resulting increase in the frequency and severity of climate-related phenomena are very substantial sources of risk. While government aid can act as a type of insurance against climate disasters, it is not perfect due to the uncertainty of government policy. Thus, there is a greater need for preventive measures by the businesses that investors own. This can be accomplished by voluntarily adopting more efficient technologies that produce fewer greenhouse gases, changing operations to be less dependent on a single supply chain, and using climate-related derivative contracts. It also implies that restricting the power of the government to borrow and tax, while it may boost firm earnings in the short run, causes the firm to face higher capital costs in the future.

For policymakers, there is a clear dilemma. On the one hand, there is a greater need for certainty to reduce the uncertainty of government response to climate-related disasters. A more firm and clear commitment would help. For example, if the government wants to promote the use of individual insurance to offset climate-related disasters, then it must take active steps to ensure that there are deep and competitive insurance markets. On the other hand, there is the question of the distributional effects of the government acting as a guarantor and the resulting future political effects they may have.

7. Patents

There are no patents associated with this work.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available in Gregory (2023).

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Stationary Conditions

To make the model stationary, I define $\widetilde{c_t} = \frac{c_t}{z_t}$, $\widetilde{x_t} = \frac{x_t}{z_t}$, $\widetilde{w_t} = \frac{w_t}{z_t}$, $\widetilde{k_t} = \frac{k_t}{z_t}$, $\widetilde{k_t^*} = \frac{k_t^8}{z_t}$, $\widetilde{y_t} = \frac{y_t}{z_t}$, $\widetilde{U_t} = \frac{U_t}{z_t}$, $\widetilde{U_{c,t}} = \frac{U_{c,t}}{z_t}$, $\widetilde{U_{lt}} = \frac{U_{lt}}{z_t}$, $\widetilde{V_t} = \frac{V_t}{z_t}$, $\widetilde{g_t} = \frac{g_t}{z_t}$, $\widetilde{n_t} = \frac{n_t}{z_t}$, $\widetilde{A_t} = \frac{A_t}{A_{t-1}}$, $\widetilde{\lambda_t} = \lambda_t z_t^{\psi}$, and $\widetilde{q_t} = q_t z_t^{\psi}$.

$$\left(\frac{\widetilde{V_t}}{\widetilde{V}^{ss}}\right)^{1-\psi} = \left(\frac{\widetilde{U_t}}{\widetilde{U}^{ss}}\right)^{1-\psi}\left(\frac{\widetilde{U}^{ss}}{\widetilde{V}^{ss}}\right)^{1-\psi} + \beta(\theta)E_t\left(\left(\frac{\widetilde{V_{t+1}}}{\widetilde{V}^{ss}}\right)^{1-\gamma}\hat{z}_{t+1}^{1-\gamma}\right)^{\frac{1-\psi}{1-\gamma}}$$

$$\widetilde{U_t} = \widetilde{c}_t(1-l_t)^v$$

$$\widetilde{U_{c,t}} = (1-l_t)^v$$

$$\widetilde{U_{l,t}} = -v\widetilde{c}_t(1-l_t)^{v-1}$$

$$(1-\psi)\left(\widetilde{U_t}\right)^{-\psi}\widetilde{U_{l,t}} = \widetilde{\lambda}_t\widetilde{w_t}$$

$$(1-\psi)\left(\widetilde{U_t}\right)^{-\psi}\widetilde{U_{c,t}} = \widetilde{\lambda}_t$$

$$M_{t+1} = (\beta_0[1 - p_{d,t} + p_{d,t}exp((1-\gamma)ln(1-\theta_t))]^{\frac{1-\psi}{1-\gamma}} \frac{\lambda_{t+1}}{\lambda_t}(\widehat{z_t})^{-\psi} \frac{\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{\psi-\gamma}(\widehat{z_{t+1}})^{\psi-\gamma}}{E_t\left(\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{1-\gamma}(\widehat{z_{t+1}})^{1-\gamma}\right)^{\frac{\psi-\gamma}{1-\gamma}}}$$

$$\widetilde{y_t} = \widetilde{c_t} + \widetilde{x_t}$$

$$\widetilde{q_t^f} = E_t M_{t+1}$$

$$\widetilde{q_t^e} = E_t\left(M_{t+1}\left(\widetilde{div_{t+1}} + \widetilde{q_{t+1}^e}\right)\right)$$

$$\widetilde{k_t^*} = (1-\delta)\widetilde{k_t} + \left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\widehat{z_t}\right)\widetilde{x_t}$$

$$\widetilde{k_t} = \frac{\widetilde{k_t^*}}{\widehat{z_t}}\exp(-d_t\theta_t)$$

$$\widetilde{div_{i,t}} = p_t\widetilde{y_{i,t}} - \widetilde{w_{i,t}}l_{i,t} - \widetilde{x_{i,t}} - \widetilde{n_{i,t}}\widetilde{e_{i,t}}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_R}\left(\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_\Pi}\left(\frac{\frac{\widetilde{y_t}}{\widetilde{y_{t-1}}}\widehat{z_t}}{exp(\Lambda_y)}\right)^{\gamma_y}\right)^{1-\gamma_R} exp(m_t)$$

$$1 = E_t M_{t+1}\frac{R_t}{\Pi_{t+1}}$$

$$E_t(M_{t+1}exp(-d_t\theta_t)[\widetilde{r}_{t+1} + \widetilde{q}_{t+1}(1-\delta)]) = \widetilde{q}_t$$

$$1 = \widetilde{q}_t\left[1 - S\left[\frac{x_t}{x_{t-1}}\right]\widehat{z_t} - S'\left[\frac{x_t}{x_{t-1}}\right]z_t\widehat{\left[\frac{x_t}{x_{t-1}}\right]}\widehat{z_t}\right] + E_t\left(M_{t+1}\widetilde{q}_{t+1}S'\left[\frac{x_t}{x_{t-1}}\right]z_t\left(\widehat{\left[\frac{x_t}{x_{t-1}}\right]}\widehat{z_t}\right)^2\right)$$

$$\widetilde{y_t} = \frac{\widehat{A_t}}{\widehat{z_t}}\left(\widetilde{k_t^*}exp(-d_t\theta_t)\right)^{\alpha} l_t^{\zeta} e_t^{1-\alpha-\zeta} - \phi$$

$$\widetilde{r_t} = A_t\alpha\left(\widetilde{k_t^*}exp(-d_t\theta_t)\right)^{\alpha-1} l_t^{\zeta} e_t^{1-\alpha-\zeta}$$

$$\widetilde{w_t} = \frac{\widehat{A_t\zeta}}{\widehat{z_t}}\left(\widetilde{k_t^*}exp(-d_t\theta_t)\right)^{\alpha} l_t^{\zeta-1} e_t^{1-\alpha-\zeta}$$

$$\widetilde{n_t} = (1-\alpha-\zeta)\frac{\widehat{A_t}}{\widehat{z_t}}\left(\widetilde{k_t^*}exp(-d_t\theta_t)\right)^{\alpha} l_t^{\zeta-1} e_t^{-\alpha-\zeta}$$

$$p_t = \left(\frac{1}{\alpha}\right)^{\alpha}\left(\frac{1}{\zeta}\right)^{\zeta}\left(\frac{1}{1-\alpha-\zeta}\right)^{1-\alpha-\zeta} \widetilde{r_t^{\alpha}}\widetilde{w_t^{\zeta}}\widetilde{n_t^{1-\alpha-\zeta}}$$

$$\frac{\widetilde{k_t}}{l_t} = \frac{\alpha}{\zeta}\frac{\widetilde{w_t}}{\widetilde{r_t}}$$

$$\frac{\widetilde{k_t}}{\widetilde{e_t}} = \frac{\alpha}{1-\alpha-\zeta}\frac{\widetilde{n_t}}{\widetilde{r_t}}$$

$$\widetilde{q_t^f} = E_t(M_{t+1})$$

$$\widetilde{q_t^f} = E_t\left(\beta_0[1 - p_{d,t} + p_{d,t}exp((1-\gamma)ln(1-\theta_t))]^{\frac{1-\psi}{1-\gamma}}\frac{\lambda_{t+1}}{\lambda_t}(\widehat{z_t})^{-\psi}B\right)$$

$$B = \frac{\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{\psi-\gamma}(\widehat{z_{t+1}})^{\psi-\gamma}}{E_t\left(\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{1-\gamma}(\widehat{z_{t+1}})^{1-\gamma}\right)^{\frac{\psi-\gamma}{1-\gamma}}}$$

By Equation (A40), the stochastic discount factor and substitution are defined.

Appendix B

Appendix B.1. The Representative Household

A representative household's preferences are represented using an Epstein–Zin aggregator between the current period utility U_t and the continuation utility V_{t+1}:

$$V_t^{1-\psi} = U_t^{1-\psi} + \beta E_t \left(V_{t+1}^{1-\gamma} \right)^{\frac{1-\psi}{1-\gamma}} \tag{A1}$$

where the period utility over consumption c_t and labor l_t is detailed as $U_t = c_t(1-l_t)^v$. E_t is the conditional expectations operator. γ is the parameter of risk aversion. The intertemporal elasticity of substitution (IES) is given by $\frac{1}{\hat{\psi}}$, where $\hat{\psi} = (1-v)(1-\psi)$, after Gourio (2012).

The representative household's budget constraint is:

$$c_t + x_t + \frac{b_{t+1}}{p_t} + \varsigma\theta_t = w_t l_t + r_t k_t + R_{t-1}\frac{b_t}{p_t} + div_t + T_t \tag{A2}$$

where x_t is the investment in capital, w_t is the wage, r_t is the rental price of capital, div_t are the dividends (profits) of the firm in the economy, and $\varsigma\theta_t$ is the household cost due to the overall climactic disasters, with $\varsigma > 0$. The household trades a nominal bond b_t that pays a gross return of R_t. T_t is a lump-sum net transfer from the government. The nominal bond is transformed into real quantities by dividing it by the price p_t of the produced good. Also, there is a full set of Arrow securities, but assuming complete markets and a net-zero supply condition for those securities, these can be omitted from the budget constraint.

Capital evolves over time according to the following rules:

$$k_t^* = (1-\delta)k_t + \left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\right)x_t \tag{A3}$$

$$logk_t = logk_{t-1}^* - d_t\theta_t \tag{A4}$$

where the occurrence of a disaster will destroy a proportion d_t of the capital stock due to physical damage.

I define the state of the economy using the endogenous variables $log\,\widetilde{k}_{t-1}^*$, $log\widetilde{x}_{t-1}$, $log\Pi_{t-1}$, $log\widetilde{y_{t-1}}$, and $logR_{t-1}$ and the exogenous variables d_t, $log\theta_t$, $z_{A,t}$, and m_t.

The stationary representation of the risk-free rate is

$$S\left[\frac{x_t}{x_{t-1}}\right] = \frac{\kappa}{2}\left(\frac{x_t}{x_{t-1}} - \Lambda_x\right)^2 \tag{A5}$$

where δ is the non-disaster-related rate of physical depreciation of capital. k_{t-1}^* is the capital decision taken by the household in period $t-1$. $S[\,]$ is an increasing and concave function, of which the curvature captures adjustment costs. θ_t is the disaster shock.

The evolution of θ_t is specified in logs in order to ensure $\theta_t > 0$ for all t:

$$log\theta_t = (1-\rho_\theta)log\overline{\theta} + \rho_\theta log\theta_{t-1} + \rho_g \log(g_t) + \sigma_\theta\epsilon_{\theta,t} + \omega_g\varepsilon_{g,t}$$

$$\epsilon_{\theta,t} \sim N(0,1), \varepsilon_{g,t} \sim U(log(g_t)) \tag{A6}$$

In addition to varying with the level of change of CO_2, g_t, Equation (A6) is time varying due to the AR structure to the log of θ_t. It also has an ambiguous component $\omega_g\varepsilon_{g,t}$ that is suspected to rise over time with the level of carbon dioxide. An AR(1) process is assumed for $log\theta_t$ in contrast to the propositions of Lemoine and Traeger (2016) and Cai and Lontzek (2019); the evidence below shows that the process for economic damages from disasters is stationary, so the evidence points to the process for the evolution of θ_t

being stationary. The time- and CO_2 level-varying structures for the probability of disaster, p_d, are specified as:

$$logp_{d,t} = (1-\rho_d)log\overline{p_d} + \rho_d logp_{d,t-1} + \rho_{gd}\log(g_t) + \sigma_d\epsilon_{d,t}, +\omega_d\varepsilon_d$$

$$\epsilon_{d,t} \sim N(0,1),\ \varepsilon_d \sim U(\log(g)) \tag{A7}$$

Again, as with the level of damage θ_t, the probability of disaster, $p_{d,t}$, is also determined by a random component whose distribution is known, $\epsilon_{d,t} \sim N(0,1)$, and a component that is unknown but is suspected to be related to the level of carbon dioxide in the atmosphere, $\varepsilon_d \sim U(\log(g)$. Again, the evidence presented below suggests that the probability of disaster is stationary, so an AR(1) process is assumed. This equation assumes that the probability of disasters rises with the level of greenhouse gases, as suggested by the recent results of climate modeling by Fischer et al. (2021).

The household maximizes its preferences (A1) subject to the budget constraint (A2) and the law of motion for capital (A3). The resulting optimality conditions are:

$$E_t(M_{t+1}\exp(d_{t+1}\theta_{t+1})[r_{t+1} + q_{t+1}(1-\delta)]) = q_t \tag{A8}$$

$$1 = q_t\left[\left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\right) - S'\left[\frac{x_t}{x_{t-1}}\right]\frac{x_t}{x_{t-1}}\right] + E_t\left(M_{t+1}\left[q_t S'\left[\frac{x_t}{x_{t-1}}\right]\left(\frac{x_t}{x_{t-1}}\right)^2\right]\right) \tag{A9}$$

$$\frac{vc_t}{(1-l_t)} = w_t \tag{A10}$$

where M_{t+1} is the stochastic discount factor:

$$M_{t+1} = \beta\frac{\lambda_{t+1}}{\lambda_t}\frac{V_{t+1}^{\psi-\gamma}}{E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{\psi-\gamma}{1-\gamma}}}$$

and λ_t is the Lagrange multiplier associated with the budget constraint, and q_t is the Lagrange multiplier associated with the evolution of the law of capital. A non-arbitrage condition determines the nominal gross returns on bonds as:

$$1 = E_t M_{t+1}\frac{R_t}{p_{t+1}} \tag{A11}$$

Appendix B.2. The Firms

There is a continuum of differentiated goods producers that combine capital, labor, and a level of carbon-emitting natural resources e_t in a production function:

$$y_{i,t} = max\left\{A_t k_{i,t}^{\alpha} l_{i,t}^{\zeta} e_{i,t}^{1-\alpha-\zeta} - \phi z_t, 0\right\} \tag{A12}$$

The common neutral technological level A_t follows a random walk with drift in logs:

$$logA_t = logA_{t-1} + \Lambda_A + \sigma_A\epsilon_{A,t} - \zeta d_t\theta_t,\ \epsilon_{A,t} \sim N(0,1) \tag{A13}$$

which is subject to a Gaussian shock $\epsilon_{A,t}$ and the rare disaster shock d_t with the time-varying impact of θ_t.

Disasters reduce the physical capital and total output by the same factor as shown in the studies by Gabaix (2011) and Gourio (2012). The common fixed cost, ϕz_t, is indexed by a measure of technology, $z_t = A_t^{\frac{1}{\zeta}}$, to ensure it remains relevant over time.

Factor prices are determined by their marginal product:

$$r_{i,t} = \alpha A_t k_{i,t}^{\alpha-1} l_{i,t}^{\zeta} e_{i,t}^{1-\alpha-\zeta} \tag{A14}$$

$$w_{i,t} = \zeta A_t k_{i,t}^{\alpha} l_{i,t}^{\zeta-1} e_{i,t}^{1-\alpha-\zeta} \tag{A15}$$

$$n_{i,t} = (1-\alpha-\zeta) A_t k_{i,t}^{\alpha} l_{i,t}^{\zeta} e_{i,t}^{-\alpha-\zeta} \tag{A16}$$

where $n_{i,t}$ is the cost of transforming the carbon emitting natural resources $e_{i,t}$.

Firms seek to maximize the dividend, $div_{i,t}$:

$$div_{i,t} = p_t y_{i,t} + t_{i,t} - w_{i,t} l_{i,t} - x_{i,t} - n_{i,t} e_{i,t} - \varphi \theta_t \tag{A17}$$

where φ represents the cost from rebuilding from shock θ_t, which varies over time. $t_{i,t}$ represents lump-sum net transfers from the government. Of course, in this model, there is no social cost of carbon, other than the cost due to disasters caused by the changes in the overall carbon dioxide level.

Appendix B.3. The Monetary Authority

The monetary authority sets the nominal interest rate according to the Taylor Rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\gamma_R} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\gamma_\Pi} \left(\frac{\frac{y_t}{y_{t-1}}}{\exp(\Lambda_y)}\right)^{\gamma_y} \right)^{1-\gamma_R} \exp(\sigma_m \epsilon_{m,t}),\ \epsilon_{m,t} \sim N(0,1) \tag{A18}$$

$\epsilon_{m,t}$ is a monetary shock. Π_t is realized inflation, equal to $\frac{p_t}{p_{t-1}}$. Π is the target level of inflation, and R is the implicit target for the nominal gross return of bonds (which depends upon Π, β, and the growth rate Λ_y along the balanced growth path of the model). The proceedings from monetary policy are distributed as a lump sum to the representative household.

Appendix B.4. Aggregation

The aggregate resource constraint is given by:

$$c_t + x_t = \frac{1}{p_t}\left(A_t k_{i,t}^{\alpha} l_{i,t}^{\zeta} e_{i,t}^{1-\alpha-\zeta} - \phi z_t\right) \tag{A19}$$

Appendix B.5. Asset Prices

Disasters have a large impact on asset prices, particularly with ambiguous distributions, as demonstrated by Backus et al. (2015). So, even given small economic values of climatic disasters, there can be enormous implications for asset prices. There are three asset-pricing implications of the model. First, the price of a one-period, risk-free real bond, q_t^f, is

$$q_t^f = E_t(M_{t+1}) \tag{A20}$$

Second, the price of a claim to the stream of dividends, which is called equity, is equal to:

$$q_t^e = E_t\left(M_{t+1}\left(div_{t+1} + q_{t+1}^e\right)\right) \tag{A21}$$

The household that owns the physical capital and rents it to firms is specified. Given the assumption of complete markets, this is equal to the firm owning the physical capital and the household owning these claims to dividends.

Third, the price earnings (or price-dividend ratio) are defined as:

$$\frac{q_t^e}{div_t} = E_t\left(M_{t+1}\left(\frac{div_{t+1}}{div_t}\left(1 + \frac{q_{t+1}^e}{div_{t+1}}\right)\right)\right) \tag{A22}$$

Appendix B.6. The Environment

A firm's emittance of CO_2, $e_{i,t}$, contributes to the environmental level of change of CO_2, g_t, through the following function based on Solomon et al. (2008):

$$g_t = \tau_1 g_{t-1} + \tau_2 \sum_{i=1}^{n} e_{i,t} + \sum_{j=3}^{m} \tau_j \vartheta_j + \sigma_g \epsilon_{g,t}\,,\ \epsilon_{g,t} \sim N(0,1) \tag{A23}$$

where τ_1 and τ_2 are the fractions of emittances going into the environment long term. $\epsilon_{g,t}$ is a term that accounts for other sources of CO_2. ϑ_j are other factors that may affect the level of change in CO_2.

Appendix B.7. The Government

The government decision-making process is modeled similar to Pástor and Veronesi (2013). A major difference in this model over Pástor and Veronesi (2013) is that in the current model, the government does not have contemporary information on household wealth, but it does have current information on the change in average firm profitability through earnings announcements, stock market data, and industry trends, etc. Therefore, the government seeks to maximize, through its policies, the change in the profitability of the average firm as a proxy of investor wealth:

maxn∈{0,. . .N}EtC^ndivi,tt1-γ1-γpolicy ti,t (A24)

where C^n is the cost if policy n is adopted by the government. If C^n > 1, then the policy is costly to the government, perhaps in the sense of losing political power or losing an election. If C^n < 1, then the policy is beneficial to the government. Uncertainty about C^n, represented by \sigma_c, is the source of political uncertainty in the model. The initial C^0 is normalized to 1 for convenience; thus, initially, retaining the existing policy has no costs or benefits to the government. The assumption that the government seeks to maximize current period wealth is supported by the work of Wisniewski et al. (2012), who found that the P/E ratio of the market is strongly positively associated with presidential approval ratings (with a higher approval associated with less uncertainty), further work by Gilens and Page (2014) shows that the government seeks to maximize the interests of businesses over households. When the government decides on new policies, the political costs of the new policy are revealed in that period to all agents at time τ. At time 0, the a priori distribution of C^n is:

$$C^n \equiv (\log(C^n) \sim N = \{1,\ldots,N\})\left(\frac{1}{2}\sigma_c^2\right) for\ t_{i,t} \tag{A25}$$

$$\sigma_c^2 = f(C^n, ddiv_{i,t}) \tag{A26}$$

The C^n values will be uncorrelated across government policy choices and independent of the Brownian motions in Equation (2). Due to the uncertainty of political costs, the market risk premium before time τ responds to political uncertainty. σ_c^2, political uncertainty, is a function of both political cost and the average profitability of the firm. Generally, the more profitable firms have a lower likelihood of a policy change. The less profitable firms are, the greater the likelihood of a policy change, so there is an inverse relationship between $d\Pi_t$ and σ_c^2. Of course, since based on (17), profitability is affected by disaster shocks, the likelihood of policy change is also affected by the occurrence of disasters.

Appendix B.8. Euler Conditions

The household's maximization problem is defined as follows:

$$\max_{c_t, k_t^*, x_t l_t} \left\{ U_t^{1-\psi} + \beta E_t \left(V_{t+1}^{1-\gamma} \right)^{\frac{1-\psi}{1-\gamma}} \right\} \tag{A27}$$

$$s.t.\ c_t + x_t + \frac{b_{t+1}}{p_t} - \varsigma g_t - w_t l_t - r_t k_t - R_{t-1}\frac{b_t}{p_t} - div_t - t_{i,t} = 0_t$$

$$k_t^* - (1-\delta)k_t - \left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\right)x_t = 0$$

$$k_{t+1} = k_t^* exp(-d_{t+1}\theta_{t+1})$$

where the value function V_t depends upon the household's actual stock of capital k_t and on past investments x_{t-1}, as well as on aggregate variables and shocks that the household takes as given. Among these are the household's net exposure to the overall pollution level ςg_t, which can be thought of as an insurance premium against health complications arising from the overall level of pollution that all households are exposed to over the course of a life.

$V_{k,t}$ and $V_{x,t}$ are defined as the respective derivatives of V_t to k_t and x_{t-1}, assuming differentiability. Using the envelope theorem:

$$(1-\psi)V_t^{-\psi}V_{k,t} = \lambda_t r_t + Q_t(1-\delta) \tag{A28}$$

$$(1-\psi)V_t^{-\psi}V_{x,t-1} = Q_t Q_t S'\left[\frac{x_t}{x_{t-1}}\right]\left(\frac{x_t}{x_{t-1}}\right)^2 \tag{A29}$$

The third budget constraint is excluded, substituting directly into the value function of the other constraints as necessary.

Differentiating the Lagrangian with respect to c_t, x_t, l_t, and k_t^* yields the following first-order conditions:

$$(1-\psi)U_t^{-\psi}U_{c,t} = \lambda_t \tag{A30}$$

$$(1-\psi)\beta E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{\gamma-\psi}{1-\gamma}} E_t(V_{t+1}^{-\gamma}V_{k,t+1}exp(-d_{t+1}\theta_{t+1})) = Q_t \tag{A31}$$

$$\lambda_t = Q_t\left[\left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\right) - S'\left[\frac{x_t}{x_{t-1}}\right]\frac{x_t}{x_{t-1}}\right] + (1-\psi)E_t\left(V_{t+1}^{1-\gamma}\right)^{\frac{\gamma-\psi}{1-\gamma}} E_t\left(V_{t+1}^{-\gamma}V_{k,t+1}\right) \tag{A32}$$

$$(1-\psi)U_t^{-\psi}U_{l,t} = \lambda_t w_t \tag{A33}$$

Appendix B.9. The Stationary Representation of the Model

To make the model stationary, the following are defined:

$$\widetilde{c_t} = \frac{c_t}{z_t},\ \widetilde{x_t} = \frac{x_t}{z_t},\ \widetilde{w_t} = \frac{w_t}{z_t},\ \widetilde{k_t} = \frac{k_t}{z_t},\ \widetilde{k_t^*} = \frac{k_t^8}{z_t},\ \widetilde{y_t} = \frac{y_t}{z_t},\ \widetilde{U_t} = \frac{U_t}{z_t},\ \widetilde{U_{c,t}} = \frac{U_{c,t}}{z_t},$$

$$\widetilde{U_{lt}} = \frac{U_{lt}}{z_t},\ \widetilde{V_t} = \frac{V_t}{z_t},\ \widetilde{g_t} = \frac{g_t}{z_t},\ \widetilde{n_t} = \frac{n_t}{z_t},\ \widetilde{A_t} = \frac{A_t}{A_{t-1}},\ \widetilde{\lambda_t} = \lambda_t z_t^{\psi},\text{ and } \widetilde{q_t} = q_t z_t^{\psi}$$

Other re-scaled variables will be introduced in Appendix A in the model conditions. Lastly, the detrended utility variables are normalized by their steady-state value to avoid scaling problems.

The following state variables are defined to make them linear in the shocks:

$$d_{t+1} = \mu^d + \left(\epsilon_{d,t+1} - \mu^d\right) \tag{A34}$$

$$log\theta_{t+1} = (1-\rho_\theta)log\overline{\theta} + \rho_\theta log\theta_t + \rho_g \log(g_{t+1}) + \sigma_\theta\epsilon_{\theta,t+1}, \tag{A35}$$

$$z_{A,t+1} = \sigma_A\epsilon_{A,t+1} \tag{A36}$$

$$m_{t+1} = \sigma_m\epsilon_{m,t+1} \tag{A37}$$

The stationary conditions are given in Appendix A.

The following variables depend only on the exogenous variables:

$$log\widehat{A_t} = \Lambda_A + z_{A,t} - (1-\alpha)d_t\theta_t \tag{A38}$$

$$log\hat{z}_t = \frac{1}{1-\alpha} log\widehat{A_t} \tag{A39}$$

which means that the long-run path of the level of technology and the long-run path of the level of fixed costs can be affected by the occurrence of climate-related disasters.

Appendix B.10. The Discount Factor and Returns

Following Gourio (2012) and Isoré and Szczerbowicz (2017), with detrending, the discount factor becomes:

$$\beta(p_{d,t}) = \beta_0[1 - p_{d,t} + p_{d,t}\exp((1-\gamma)\ln(1-\theta_t))]^{\frac{1-\psi}{1-\gamma}} \tag{A40}$$

where β_0 is the discount factor without adjustment due to time-varying disasters.

Thus, an unexpected change in the disaster risk will drive macroeconomic quantities and asset prices through a combination of first- and second-moment effects on the discount factor. In the current model, this also holds true for disaster risk due to the rising level of pollution.

From Appendix A, the stationary representation of the risk-free rate is:

$$\widetilde{q}_t^f = E_t M_{t+1} = E_t\left(\beta_0[1 - p_{d,t} + p_{d,t}\exp((1-\gamma)\ln(1-\theta_t))]^{\frac{1-\psi}{1-\gamma}} \frac{\boldsymbol{\lambda}_{t+1}}{\lambda_t} (\widehat{z_t})^{-\psi} B\right) \tag{A41}$$

$$B = \frac{\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{\psi-\gamma} (\widehat{z_{t+1}})^{\psi-\gamma}}{E_t\left(\left(\frac{\widetilde{V}_{t+1}}{\widetilde{V}_{ss}}\right)^{1-\gamma} (\widehat{z_{t+1}})^{1-\gamma}\right)^{\frac{\psi-\gamma}{1-\gamma}}}$$

It follows the return on a stock as:

$$\begin{gathered} \widetilde{q}_t^e = E_t\left(M_{t+1}\left(\widetilde{div_{t+1} + \widetilde{q_{t+1}^e}}\right)\right) = \\ E_t(\beta_0[e[1 - p_{d,t} + p_{d,t}exp((1-\gamma)ln(1-\theta_t))]^{\frac{1-\psi}{1-\gamma}} \tfrac{\lambda_{t+1}}{\lambda_t} (\widehat{z_t})^{-\psi} B)(p_t\widetilde{y}_{i,t} + \\ t_t(\sigma_c^2, \theta_t) - \widetilde{w_{i,t}}l_{i,t} - \widetilde{x_{i,t}} - n_{i,t}e_{i,t} - \varphi\theta_t) + \widetilde{q_{t+1}^e} \end{gathered} \tag{A42}$$

So clearly, the return on a stock is influenced by θ_t, the size of the disaster shock. It is also clearly influenced by the size of the lump sum payment of the government to firms t_t, which, in turn, will also be influenced by the size of the disaster shock and the uncertainty of the government policy response. In effect, there are three factors of uncertainty: the disaster shock θ_t, the government uncertainty response σ_c^2, and the combined government uncertainty response and disaster shock $\theta_t\sigma_c^2$.

Appendix C.

VAR Model of the EV Variable

Next, I establish the empirical support that carbon dioxide levels are associated with the economic value of damages due to climatic disasters in the US.

The stationarity of the four variables allows for the examination of the interaction of the four variables via a vector-autoregression model, as allowed in the model. A four-equation VAR(2) model is used, where $Y_t = C + A_1Y_{t-1} + A_2Y_{t-2} + e_t$:

$$Y_t = [EV_t, DCO_t, NI_t, S_t]$$

$$A_1 = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ 0 & a_{32} & a_{33} & a_{34} \\ 0 & 0 & 0 & a_{44} \end{bmatrix}$$

And A_2 is similarly restricted. This means that past shocks to economic damages affect economic damages and changes to carbon dioxide levels but nothing else. This is reasoned to occur with that economic damages may carry over from month to month and that rebuilding may add to carbon dioxide production. Past shocks to changes in the carbon dioxide level are allowed to affect economic damages due to climatic disasters, future changes in carbon dioxide levels, and the El Nino effect. Past shocks to the El Nino effect are allowed to affect everything, but sunspots are allowed to affect everything as a proxy for solar activity.

Table A1 exhibits the results of the GLS estimation of the VAR.

Table A1. VAR model of the exogenous variables. The table exhibits the estimated parameters, standard errors, and associated statistics from the estimation of a four-equation VAR(2) model as described in the text. EV is the log of the economic value of monthly climatic disasters, DCO is the monthly change in atmospheric carbon dioxide levels, S is the monthly number of average daily sunspots, and NI is the monthly El Nino effect as detailed in the text. The estimation uses generalized least squares. Standard errors are shown in ( ) and t-statistics in [ ].

	EV	**DCO**	**NI**	**S**
	0.074832	−57.21466		
EV_{t-1}	(0.04863)	(36.0024)		
	[1.53896]	[−1.58919]		
	0.019617	−2.354077		
EV_{t-2}	(0.04846)	(35.8820)		
	[0.40478]	[−0.06561]		
	1.88×10^{-5}	1.202773	−0.005216	
DCO_{t-1}	(5.0×10^{-5})	(0.03702)	(0.00777)	
	[0.37694]	[32.4894]	[−0.67113]	
	0.000151	−0.662929	0.003683	
DCO_{t-2}	(5.1×10^{-5})	(0.03742)	(0.00779)	
	[2.98882]	[−17.7174]	[0.47310]	
	−0.000329	0.054305	1.775174	
NI_{t-1}	(0.00017)	(0.12910)	(0.02766)	
	[−1.88442]	[0.42064]	[64.1717]	
	0.000352	−0.066774	−0.825262	
NI_{t-2}	(0.00017)	(0.12898)	(0.02764)	
	[2.02286]	[−0.51771]	[−29.8524]	
	7.86×10^{-7}	−0.000464	0.000169	0.657907
S_{t-1}	(1.5×10^{-6})	(0.00108)	(0.00023)	(0.04677)
	[0.53746]	[−0.42896]	[0.72584]	[14.0656]
	-6.98×10^{-7}	0.000365	−0.000179	0.296455
S_{t-2}	(1.5×10^{-6})	(0.00108)	(0.00023)	(0.04680)
	[−0.47737]	[0.33700]	[−0.76842]	[6.33402]
	0.000234	−0.049530	0.002608	3.411433
C	(5.6×10^{-5})	(0.04149)	(0.00858)	(1.70946)
	[4.17207]	[−1.19388]	[0.30391]	[1.99562]
R^2	0.077131	0.742124	0.982587	0.883383
Wald test stat	1.519033	1.043275	1.59289	1.87849

The results show that past shocks to changes in the carbon dioxide level are a significant factor in the economic damages due to climatic disasters with a two-month lag. The El Nino effect is also significant, decreasing the value of economic damages due to climatic disasters but reverses itself in the second lag. The proxy for solar activity is not significant in either lag. The R^2 for the economic value of damages due to climatic disasters is low, 0.077131, compared to the other equations, indicating other factors may be neglected. The

Wald tests show the null hypothesis that the equations are correctly specified and cannot be rejected.

To further understand the relationship between the carbon dioxide level and the economic damages due to climatic disasters, a series of Granger causality tests are run, controlling for the other exogenous variables. The results are exhibited in Table A2.

Table A2. Causality tests of climate-related economic damages to changes in atmospheric carbon dioxide levels. "Controlling EV only" is the model where only EV, the economic damage due to climate-related disasters and DCO as well as the change in carbon dioxide levels are included in the Granger causality test. The second test is the block exogeneity test for the causality of DCO on EV controlling for the effects of S and N in the VAR estimated above. It uses a Chi-square test. EV: the economic value of damages due to climatic disasters. DCO is the monthly change in atmospheric carbon dioxide levels, S is the monthly number of average daily sunspots, and NI is the monthly El Nino effects, as detailed in the text.

Test	**F Statistic**	**Probability**
Controlling EV only	11.2486	0.000002
	Chi-square statistic	Probability
Block exogeneity test	23.24886	0.000009

As Table 3 shows, at conventional levels of significance, it cannot be rejected that changes in the carbon dioxide level Granger-cause the economic value of damages due to climatic disasters, even when controlling for the El Nino Effect and solar activity. Thus, it is concluded that changes in carbon dioxide levels have a small but significant causal relationship with the economic value of climatic damages in the United States over this period.

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