How climate-awake are financial markets?

Galina Hale[a] , Bhavyaa Sharma[c]
[a]UCSC, NBER, CEPR*
[b]UCSC.

Abstract

As physical manifestations of climate change become more apparent, are we to expect massive asset repricing and financial destabilization? The answer to this question crucially depends on whether climate risks are priced-in already in different asset classes. Climate-related events are unique in that they are drawn from a distribution that shifts and becomes more disperse over time along an uncertain trend, making belief formation a crucial component of asset pricing. We simulate the response of asset prices to changes in the arrival rate of climate-related disasters in the context of the rare events asset pricing framework based on Gabaix (2012), in which we allow for varying degrees of climate optimism and belief rigidity. We quantify "fully priced in" response in various structures of subjective belief formation. We survey the empirical literature on the pricing of physical climate risk in equity and fixed income markets to evaluate what belief formation structures may be consistent with assumption of fully priced-in beliefs. While there is no consensus in empirical literature, our preliminary results show that in recent years, asset price responses to disasters documented in the literature are more consistent with low climate optimism and relatively low belief rigidity.

JEL classification: G12, G17, Q54
Keywords: climate risk, asset pricing, beliefs, meta-analysis

*Corresponding author: gbhale@ucsc.edu.

1 Introduction

Since the Paris United Nations Climate Change Conference of the Parties (COP21) in December 2015, the attention of financial markets to climate risks has increased substantially (Sautner et al., 2020). Not surprisingly, a surge of literature on the response of asset prices to climate risks followed (Figure 1), focusing on both physical risks arising from manifestations of changing climate and transition risks arising from changes necessary for green transition.[1] Many empirical studies found that asset prices indeed respond to various climate risks, especially after COP21. However, the question still remains whether the documented reaction of asset prices is consistent with a steady increase in awareness of climate risks or whether there is a risk of a "wake-up call" that may result in widespread asset repricing in the future. This question is central to understanding systemic financial stability risks associated with climate change and green transition. Given fundamental uncertainty about the future of climate (Barnett et al., 2020), this is not a simple question to address. Focusing on physical risks, we explicitly model belief formation in the Gabaix (2012) setting to simulate what "priced-in" response would look like in equity and fixed income markets in different belief scenarios and relate simulated response to the estimates in the literature.

Our analysis reflects the increasing frequency of disasters that is due to climate change (Stott, 2016), to which we refer to as climate shocks. There are three key differences between climate shocks and shocks traditionally modeled in asset pricing literature: first, climate shocks do not come from a fixed distribution, but rather from a distribution with mean and variance that increase over time (Seneviratne et al., 2021); second, there is fundamental uncertainty about the climate parameter that drives this distribution shift; third, uncertainty about future mitigation actions means that a variety of future climate scenarios are possible. As a result, a forward-looking asset pricing model of climate shocks needs to be explicit about the formation of beliefs about future distribution of climate shocks. We formalize belief formation with two parameters: the degree of belief rigidity, expressed as a weight in the weighted average of static beliefs and the Bayesian update in response to new climate-related weather events, and a weight associated with "optimistic" vs. "pessimistic" climate scenarios, which we calibrate to correspond to shared socioeconomic pathways SSP1 and SSP3, respectively.[2] We allow for a continuum of belief rigidity parameter — from entirely prior-conforming "climate denial" belief that assuming Poisson parameter is constant to the entirely Bayesian. We also allow for continuum of beliefs about the underlying probability of SSP1 vs. SSP3, climate optimism parameter.

Our first step is to introduce explicit belief formation into Gabaix (2012) framework. Gabaix (2008) specifically states that this type of model is suitable for application to "time-varying per-

[1] See a recent survey of the empirical literature in Campiglio et al. (2023).

[2] The SSP1 scenario predicts socioeconomic pathways with the assumption that the world moves to coordinated sustainable path with emissions cut to net zero, with the likely increase of global warming to be under 2 degree Celsius by 2100. Conversely, the SSP3 scenario is based on a steady increase in emissions with poorly coordinated local and global sustainable policies. The estimated increase in temperature will be close to 3.6 degree Celsius by 2100.

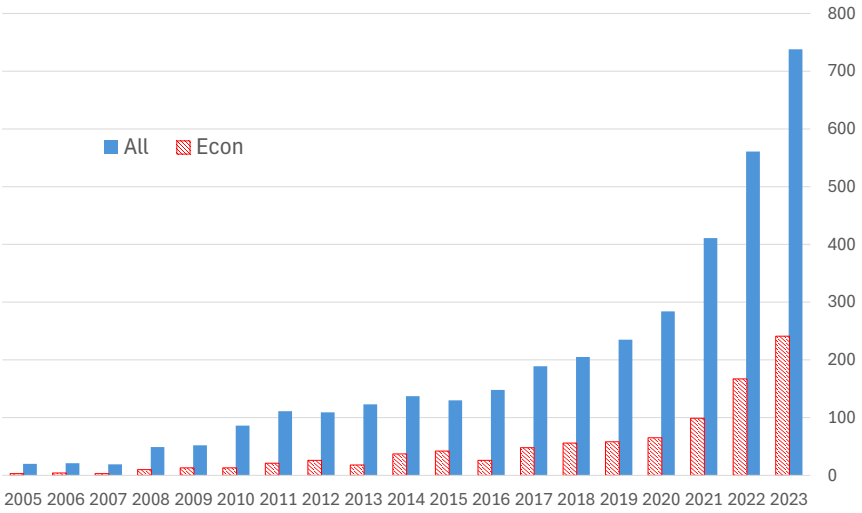


Figure 1: Number of documents containing "climate" and "finance" in Scopus

ception of risk," which is exactly our focus. Our choice of the modeling framework is also guided by the fact that Gabaix (2012) fits financial data series quite well. We follow the methodology similar to Hale (2024) to incorporate subjective disaster probability as well as expected productivity and welfare loss as a result of disasters explicitly into the model. We calibrate the model for the U.S. in 1954-1984, before the frequency of these shocks began to rise. We then simulate the model for 1985-2019 using the data on disasters from FEMA "billion dollar" disaster series. We assume that disaster arrival rate is drawn from the Poisson distribution with the parameter that is increasing over time due to an increasing frequency of weather-related disasters driven by climate change.[3] A Bayesian update of the Poisson parameter is drawn from the Gamma distribution (a conjugate prior) with observed disaster history combined with a deterministic trend that depends on the degree of climate optimism. For each combination of the resulting beliefs we simulate risk-free rate, risky bond rate, and equity premium in each year in the simulation sample. We then use simulated data to interpret empirical literature findings in the context of our model. We find that most empirical findings are consistent with low climate optimism and low belief rigidity, especially for recent data samples.

Qualitatively, the model predicts that lower climate optimism and lower belief rigidity, which correspond to higher subjective probability of a disaster, imply lower risk-free rate and higher risk premia, although the effect is not monotone with respect to combinations climate optimism for high levels of belief rigidity. The model also predicts declining risk-free rate and increasing bond and equity risk-premia over time due to increasing subjective disaster probability and disaster frequency. In addition, in disaster years the risk-free rate is always lower due to productivity losses, and the difference is larger in absolute value for low climate optimism and low belief rigidity. Risk

[3]This assumption is supported by the data Hale (2024). Higher Poisson parameter means higher disaster arrival rate as well as higher variance.

premia are always higher in disaster years, again especially for low climate optimism and low belief rigidity. Finally, risky bonds are more sensitive to belief parameters than AAA bonds.

With these quantitative findings, we turn to the literature that studied the effects of climate disasters on asset prices. There are two ways to interpret empirical papers that find zero or small response of asset prices to physical climate risks (Hong et al., 2019; Acharya et al., 2022). One interpretation is that the markets simply do not pay attention to these risks, which is a deviation from rationality. Without relying on the deviations of rationality, in the context of our model, these negative findings are consistent with either extremely rigid climate beliefs (no update) or very high degree of climate optimism or both. For the papers that find positive risk premia in response to physical climate events (Alok et al., 2020a; Huynh et al., 2020; Painter, 2020), we are able to offer the set of parameters that are consistent with the response.

This paper contributes the the rapidly growing literature on pricing of physical risks in the asset markets, and, more broadly, to the response of financial institutions to climate shocks. We view our contribution as two-fold. The methodological contribution is in terms of modeling asset prices in the presence of non-i.i.d. shocks, such as climate shocks, and explicit belief formation. The empirical contribution is in meta-analysis of the empirical literature on the response of financial market to physical climate shocks.

Note that in our analysis we abstract from the transition risk as it needs to be modeled in a different setting than the rare disaster model we employ here. That said, we believe that explicit modeling of belief formation and climate scenario uncertainty is key to understanding the context for the magnitude of the response of financial markets to transition risks.

We begin our presentation by briefly summarizing the analytical framework of Gabaix (2012) and our decomposition of the parameters of this framework in the context of belief rigidities and trend uncertainty, in which we derive asset prices (Section 2). We then calibrate the model to 1954-1984 data for the U.S. and simulate it for 1985-2019 in Sections 3 and 4. We discuss the related literature and interpret it in light of our quantitative results in Section 5 and then conclude.

2 Analytical framework

We take the set-up of Gabaix (2012) rare disasters model for asset pricing.

2.1 Gabaix (2012) framework summary

Macroeconomic environment of the model is simple: there is a representative agent with constant relative risk aversion (CRRA) γ and rate of time preference ρ that receives an infinite stream of endowment C_t that grows at the rate g_C. This gives the pricing kernel

$$M_t = e^{-\rho t} C_t^{-\gamma}. \tag{1}$$

A stream of stock-specific dividends D_{it} is subject to a mean-zero shock ε_{it} that is independent of disasters.

A disaster may happen at any time with probability p_t, which may vary over time. A disaster leads to a consumption drop in the disaster period by a factor $1 - B_t$ and dividend growth drop by a factor $1 - F_{it}$. Gabaix (2008) framework combines expected probability of disaster p, disaster-related productivity (dividend growth) loss $1 - F_{it}$ and disaster-related welfare (consumption) loss $1 - B_t$ into one "disaster resilience" parameter H_{it}.

$$H_{it} = p_t \mathrm{E}_t \left[B_{t+1}^{-\gamma} F_{i,t+1} - 1 \right], \tag{2}$$

if there is a disaster at $t+1$. This summary variable is sufficient to express all necessary real asset prices. However, to generate time-varying belief structure, we model these components separately for our calibration.

In order to price nominal bonds, Gabaix (2012) makes the following assumptions about inflation I_t. First, there is a trend inflation and variation of inflation around the trend that are independent of disasters. In addition, disasters induce firther variation in inflation through the following process.

$$\hat{I}_{t+1} = \frac{1 - I^*}{1 - I_t} \cdot \left(e^{-\phi_I} \hat{I}_t + \mathbf{1}_{Dis_{t+1}=1} J_t \right) + \varepsilon_{t+1}^I, \tag{3}$$

where $\hat{I}$ is the variation of inflation around the trend I^*, ϕ_I is the rate of mean reversion of this variation, and Dis is an indicator of disaster year. ε^I is a mean-zero shock that is independent of disasters. J is disaster-related inflation jump that follows a similar process with mean-reversion coefficient ϕ_J and mean-zero disaster-unrelated shock ε^J:

$$\hat{J}_{t+1} = \frac{1 - I_*}{1 - I_t} e^{-\phi_J} \hat{J}_t + \varepsilon_{t+1}^J. \tag{4}$$

2.2 Disaster probability

We assume that true disaster probability follows Poisson distribution with parameter θ_t that is increasing over time due to climate change. This assumption is consistent with the data as shown in Hale (2024). The rate of increase is deterministic, but unknown, and the agents form their beliefs about this rate, reflecting their climate optimism.

We model two extreme types of belief formation as well as their linear combination. On the one extreme, we have a climate denier with fully prior-conforming beliefs who does not update their beliefs regardless of disaster frequency realization, and thus $\theta_t = \theta_{t-1} \; \forall \, t$. On the other extreme, a fully rational agent updates their beliefs every period based on the observed disasters that period, a history of prior disasters, as well as their belief about a deterministic drift in the disaster arrival rate. We assume that rational agents update their beliefs in a Bayesian way by drawing a posterior

Poisson parameter from its conjugate prior Gamma distribution. For the first period, we assume an update to a calibrated initial disaster frequency a_0 so that $\theta_0 = \Gamma(a_0, 1)$ regardless of the belief update rule.

Rational agents know that θ_t has a drift g_θ, but may assign different probability to SSP1 scenario (successful climate change mitigation, low increase in θ_t) vs. SSP3 scenario (limited climate change mitigation, rapid increase in θ_t):

$$g_\theta = \lambda \cdot g_{SSP1} + (1 - \lambda) \cdot g_{SSP3}, \quad \forall\ \lambda \in [0, 1],$$

where $\lambda \in [0, 1]$ is the weight on the SSP1 scenario and is the first of our key belief parameters, which we will refer to as "climate optimism" parameter.

A fully Bayesian agent draws an update to the Poisson prior θ_{t-1} from the Gamma distribution

$$\theta_t = \Gamma\left(g_\theta \cdot \sum_{s=t_0}^{t-1} d_s + d_t,\ \frac{1}{t - t_0}\right),$$

where d_t is the number of disasters observed in t, the first term is the shape parameter and the second term is the scale parameter of the Gamma distribution.

Our second belief parameter is $\mu \in [0, 1]$, which determines the weight of prior-conforming vs. Bayesian component in the belief update equation, represented recursively:

$$\theta_t = \mu\, \theta_{t-1} + (1 - \mu)\, \Gamma\left(g_\theta \cdot \theta_{t-1} + d_t,\ \frac{1}{t - t_0}\right).$$

We refer to parameter μ as "belief rigidity" parameter.

Given θ_t, the probability of at least one disaster to be observed in year t is given by $p_t = 1 - e^{-\theta_t}$, where $\theta_t = \theta_t(\lambda, \mu)$.

In what follows, we omit the expectation operator E_t to simplify notation.

2.3 Asset pricing

We continue to follow Gabaix (2012) identically to formulate asset prices.

Risk-free rate r_t^f is determined by the "Ramsey" discount rate $\delta = \rho + \gamma g_C$ and the expected welfare loss through damages to consumption in case of a disaster:

$$r_t^f = \delta - p_t[B_t^{-\gamma} - 1]. \tag{5}$$

Return on equity and risk premium. Unconditional return on equity r^e_{it} can be expressed as

$$r^e_{it} = \delta - H_{it} - p_t[1 - F_{it}] = \delta - p_t \left[B_t^{-\gamma} F_{i,t} - 1\right] - p_t[1 - F_{it}] = \delta - p_t \left(B_t^{-\gamma} - 1\right) F_{it}, \tag{6}$$

which gives us the unconditional equity risk premium $q_{it} = r^e_{it} - r^f_t$:

$$q_{it} = p_t \left(1 - F_t\right) \left(B_t^{-\gamma} - 1\right). \tag{7}$$

Fixed income returns. Government bond risk premium π^G:

$$\pi^G_t = p_t \frac{B_t^{-\gamma} J^*}{1 + H_{\$_t}}, \tag{8}$$

where J^* is an average jump in inflation in a disaster year and $H_{\$_t}$ is the resilience of zero-coupon government bond $H_{\$_t} = p_t \left[\left(B_t^{-\gamma}\right) - 1\right]$.

We can also express the price of any nominal zero-coupon bond of maturity M:

$$Z_t(M) = (e^{-(\delta - H_{\$_t} + I^*)M}) \cdot (1 - (((1 - e^{-\psi_I M})/\psi_I) \cdot (\iota_t - I^*)) - K_M \pi_t), \tag{9}$$

where

$$K_M = \frac{\frac{1-e^{-\psi_I M}}{\psi_I} - \frac{1-e^{-\psi_J M}}{\psi_J}}{\psi_J - \psi_I}$$

and I^* is the trend of the inflation rate, ψ_I is the rate of mean reversion of inflation and ψ_J is the rate of mean reversion of the jump in inflation.

We can now express government bond yield y^G for maturity M as:

$$y^G_t(M) = -\frac{\ln Z_t(M)}{M} \tag{10}$$

and risky corporate bond yield y for maturity M and credit rating l as:

$$y_{lt}(M) = y^G_t(M) + PD_l + p_t B_t^{-\gamma} \left(1 - F_{lt}\right), \tag{11}$$

where PD_l is unconditional default probability of the bond and F_l is the disaster-related return loss specific to this credit rating.

This implies corporate bond risk premium

$$\pi_{lt}(M) = y_{lt}(M) - y^G_t(M) - PD_l. \tag{12}$$

3 Model calibration

We calibrate the model to match the data observed in 1954-1984, prior to the increase in frequency of climate-related disasters. In this version of the model the belief structure is not material, so we assume rational expectations and set p_t to be constant and derived from Poisson arrival rate estimated from the data.

Disaster probability for 1954-1984. Information on 'billion-dollar' disasters only begins in 1980, therefore, for calibration, we use dataset on disaster-related damages (adjusted to 2022 dollars) for 1954-1980 from SHELDUS. We then define "disaster years" as the years with total disaster damages (in real terms) equal to or greater than the total damages in years with at least one billion-dollar disaster observed between 1980 and 2019.

We estimate the probability of a disaster year (p) based on the occurrence of billion-dollar disasters between 1954-1984, we calculate $p_t \, \forall t = 1955, ..., 1984$ as would be estimated by a perfectly Bayesian agent, assuming initial Poisson arrival rate in 1954 is 0.0666. We arrive at the average probability of a disaster year for 1954-84 is 7.23%.

Inflation data. Using quarterly inflation data for the time period in question, we calculate that mean reversion of inflation (ϕ_i) is 0.2475, while mean reversion of inflation jumps (ϕ_j) is 1.4842. Average inflation rate during this time period was 4.23%.[4]

Other data. We set consumption growth rate to 2.5 percent as in Gabaix (2012), which corresponds to the U.S. data on GDP growth.[5]

To calculate mean reversion of the climate resilience parameter (ϕ_H), we target price-dividend ratio obtained from Global Financial Database (GFD). The procedure is described in Appendix A. We arrive at $\phi_H = 0.24$.

The rest of the parameters are derived to match exactly risk-free rate, which is 1.03 percent, equity risk premium, which is 1.89 percent, and 5-year to 1-year term premium, which is 32 basis points. The values of calibrated parameters are reported in Table 1. For simulations, we retain these parameter values, but update inflation- and disaster-related parameters.

Compared to Gabaix (2012), our calibration produces a lower rate of time preference ρ, 3.4% vs. 6.57%; higher disaster probability, 7.23% vs. 3.63%, but a slightly lower risk-adjusted disaster probability, 17.1% vs. 19.2%, which is partly due to our calibration of a lower CRRA, 3 rather than 4; higher value of sensitivity of inflation to disasters, 10% instead of 2.6%; higher average inflation in the calibration period and lower average inflation in the simulation period, with higher levels

[4]Our calibration does not require a value for J^*.

[5]GDP growth series are more appropriate for calibration than consumption growth series, because the model is an endowment economy.

of mean reversion in both periods, higher level of jump mean-reversion in calibration period and lower level in simulation period.[6]

Variable	Source	1954-84	1985-2019
Measured directly or estimated from the data			
Disaster probability (p)	Derived from data	0.0723	Simulated
Mean-reversion of inflation (ϕ_i)	Quarterly inflation data	0.2475	0.8926
Mean-reversion of inflation jumps (ϕ_j)	Quarterly inflation data	1.4842	0.4661
Average inflation (I^*)	Quarterly inflation data	4.23	2.53
Average disaster-related jump in inflation (J^*)	Quarterly inflation data	N.A.	[0.36, 2.56]
Mean-reversion of climate resilience (ϕ_H)	From price/dividend ratio	0.24	0.062
Consumption/dividend growth rate (g_C)	From Gabaix (2012) and U.S. data	0.025	0.025
Calibration results			
CRRA (γ)		3	3
Discount rate (ρ)		0.034	0.034
Productivity loss (F)		0.95	0.905
Welfare loss (B)		0.85	0.83
Sensitivity of inflation to disasters (κ)		0.1	0.1
Targeted moments (matched exactly) for 1954-84 calibration			
Mean risk free rate (r^f)	Average of end-of-the year values	0.0103	N.A.
Mean return on equity (r^e)	Average of end-of-the year values	0.0189	N.A.
Mean 5y-1y term premium	Average of end-of-the year values	0.0032	N.A.
Simulation parameters			
Belief rigidity (μ)		N.A.	[0,1]
Climate optimism (λ)		N.A.	[0,1]

Table 1: Calibration and simulation parameters

4 Model simulation for 1985-2019

We simulate the model for the period following "great moderation" which coincides with the time climate parameters started to trend upwards. We stop our simulation in 2019, to avoid the effects of COVID-19 period and a period of high inflation that followed.

4.1 Simulation set-up

To simulate the model, we collect additional data.

[6] We are unable to match the data in our calibration period with Gabaix (2012) calibration.

Disaster data. To create the paths for the disaster frequency, we rely on FEMA "billion dollar" disasters. We convert the number of observed disasters to a 0/1 indicator with 0 indicating no more than 5 disasters in a given year across the U.S. and 1 indicating 6 or more disasters. To project the series going forward, we use projections for the increase in the frequency of extreme precipitation events from IPCC6, which are 2 percent annual increase in SSP1 ($g_{SSP1} = 1.02$) and 15 percent annual increase in SSP3 ($g_{SSP3} = 1.15$), as summarized in Seneviratne et al. (2021).

Other inputs. We update inflation-related parameters from the calibration to the simulation time periods, based on the observed inflation behavior. This is important because the take-off in climate change coincided with the change in inflation and monetary policy regime in the U.S., commonly referred to as "great moderation." Thus, for the simulation we calculate that mean reversion of inflation (ϕ_i) is 0.8926, while mean reversion of inflation jumps (ϕ_j) is 0.4661. Average inflation rate during this time period was 2.53%.

We retain from our calibration values for the risk aversion coefficient $\gamma = 3$, discount rate $\rho = 0.034$, and sensitivity of inflation to disasters $\kappa = 0.1$. However, because not only frequency, but also severity of disasters is higher in our simulation period, we update values of disaster-related losses to better match the average risk-free rate and return on equity in the simulation period. Consumption-related losses increase from 15 to 17%, so that $B_{1985-2019} = 0.83$, and productivity and dividend losses increase from 5 to 9.5%, so that $F_{1985-2019} = 0.905$. While these parameters are the best to match average risk-free rate and return on equity in 1985-2019, they are also consistent with the data. In particular, recent literature estimates that damages from climatological, hydrological, and meteorological disasters in high-income countries range from 12 to 20% of GDP (Bodenstein and Scaramucci, 2024), suggesting that $B = 0.83$ is a reasonable estimate for recovery from consumption losses. We also allow for the subjective expectations of B to vary with climate optimism parameter λ, the weight investors assign to SSP1 vs. SSP3 scenario. Investors who believe in the SSP1 scenario would assume $B_{1985-2019} = 1$, that is there is only a negligible disaster loss, whereas investors who believe in the SSP3 scenario would assume $B_{1985-2019} = 0.83$, i.e., the current pace of damages to GDP. We also allow the investor to update their estimate of B once after 1984, depending on the rigidity of their beliefs. A rigid agent will hold on to their estimate of $B = 0.85$ from 1954-84, while a Bayesian agent will update their estimate to $B = B_{1980-2020} = 0.83$.

4.2 Simulation results

We present our simulation results in two ways: as time series for specific values of belief parameters $\lambda = 0.5$ and various values of μ, and as heatmaps in the λ—μ space for the average value of the outcome variables over 1985-2019 as well as for the average difference between years with and without disasters.

Figures 2 and 3 show the simulated subjective probability of disasters. We can see that the

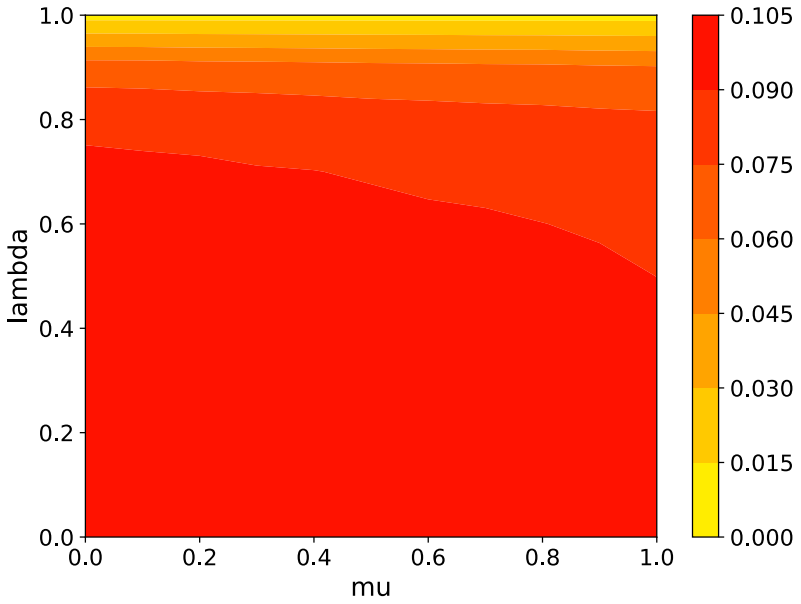


Figure 2: Average probability of disaster in simulation period

Notes: Simulated subjective probability of disasters as a function of belief rigidity μ and climate optimism λ, average across 1985-2019. Disaster probability is calculated following details in Section 2.2. Simulation parameters are in Table 1.

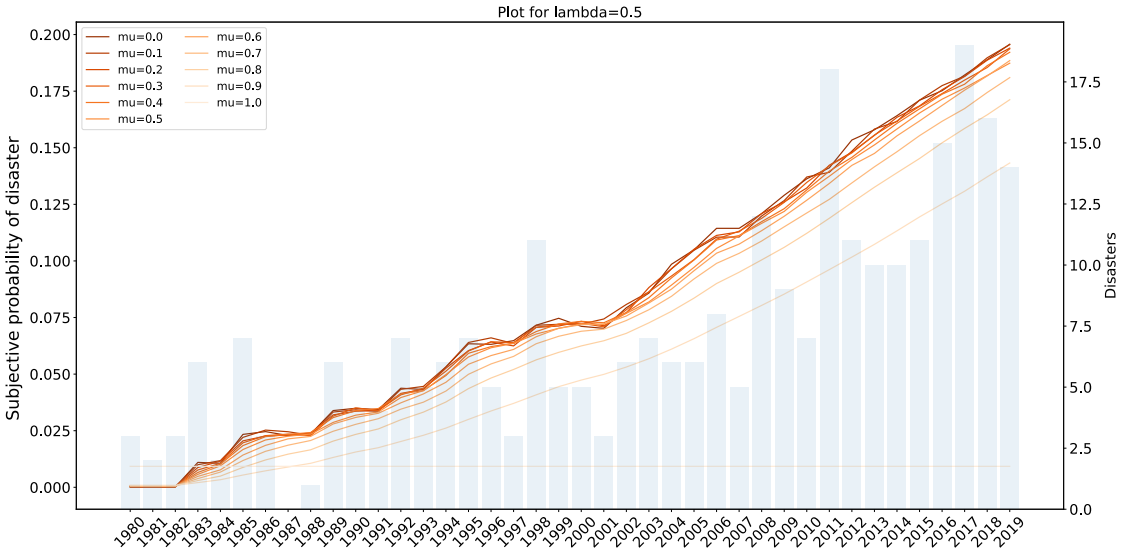


Figure 3: Probability of disaster

Notes: Simulated subjective probability of disasters as a function of belief rigidity μ, as indicated, and average climate optimism $\lambda = 0$. Disaster probability is calculated following details in Section 2.2. Simulation parameters are in Table 1.

average subjective disaster probability is mostly affected by the climate optimism — for the SSP1 scenario ($\lambda = 1$) the probability of disaster is very low, while for the SSP3 scenario ($\lambda = 0$) the probability of disaster increases to 9 percent on average during 1985-2019. The effect of belief update from belief rigidity ($\mu = 1$) to Bayesian update ($\mu = 0$) is only material if the update is towards the severe climate change (SSP3), in which case the less rigid the beliefs (lower μ), the higher is the subjective disaster probability. This is also apparent in the time series chart. For a climate denier, the subjective probability remains constant at θ_0 level ($\theta_0 = \Gamma(a_0, 1)$ where $a_0 = 0.067$ is the pre-sample disaster arrival rate estimated in Hale (2024)). With Bayesian updating, the subjective probability increases over time, and the increase is steeper for less rigid beliefs (lower values of μ).

4.3 Effect of disasters on asset prices

Given the simulated subjective disaster probability for each value of λ and μ as well as the rest of the parameters, we can calculate time series and average values for asset price measures commonly used in the literature. We can also calculate the differences between average values in disaster years and no-disaster years to match commonly estimated regression equations.

Risk-free rate

We begin with risk-free rate shown in Figure 4. Panel (a) shows the average risk-free rate in 1985-2019 as a function of belief rigidity μ and climate optimism λ, panel (b) shows the difference between disaster and non-disaster years in 1985-2019 time period, and panel (c) shows time series for different values of μ and $\lambda = 0$. We can see that the risk-free rate is increasing in climate optimism (because it is negatively associated with disaster probability), but for low values of λ it is also increasing with belief rigidity, because more rigid market participants expect lower disaster probability.

Generally, disaster year risk-free rate is lower than the risk-free rate in no-disaster years. This follows directly from the model — because of the losses in consumption, disasters reduce risk-free rate. We can see that with high climate optimism, the difference is essentially zero, and it is increasing in absolute value as λ falls. The largest difference is observed in the case when both climate optimism and belief rigidity are low, which also corresponds to the highest subjective disaster probability.

Consistent with these averages, we observe from the time series in panel (c), that except for fully rigid beliefs ($\mu = 1$), rising disaster probability leads to a downward trend in the risk-free rate, which is consistent with the data. This decline is more pronounced for less rigid beliefs. There is also difference in volatility of risk-free rates as a function of belief rigidity: less rigid beliefs (lower μ) lead to more volatile the risk-free rate in response to observed disasters. This is because each increase in the observed disaster arrival rate, leads to an update of the Poisson parameter that enters into future expectations, and this update is higher when beliefs are less rigid.

Bond pricing

Turning to risky returns, we simulate bond risk premia for AAA-rated and B-rated corporate bonds. The results are reported in Figure 5. Panels (a) and (c) report averages of AAA and B-rated bond risk premia, respectively, for 1985-2019, as a functino of μ and λ; panels (b) and (d) report differences between disaster and non-disaster years; and panel (e) and (f) report time series for $\lambda = 0$.

We can see that for corporate bonds, bond risk premium has the opposite pattern of risk-free rate, it is highest for low climate optimism and low belief rigidity. While the patterns are similar for AAA and B-rated bonds, riskly bond is much more sensitive to the belief rigidity with risk premium ranging from 1.5 to 3.9 percent. Similarly, the risk premium is higher during disaster years than in non-disaster years, especially for the risky bond — as high as 2.8 percentage points difference for the case of fully Bayesian pessimistic beliefs ($\lambda = 0$, $\mu = 0$).

Consistently, bond risk premium is rising over time (panel (c)), more steeply for risky bonds than for AAA bonds. This increase is lower for high belief rigidity, but at the low levels of belief rigidity its effect is non-monotonic. Just like risk-free rate, risk premium is more volatile, more responsive to disaster occurrence, if beliefs are less rigid.

For government bonds, many papers focus on bond prices. The most common government bond maturity in the data (in cross-country studies) is 5 years, thus we simulate 5-year government bond prices. Figure 6 shows the results. As before, panel (a) shows the average for 1985-2019 as a function of belief rigidity μ and climate optimism λ, panel (b) shows the difference between disaster and non-disaster years in 1985-2019 time period, and panel (c) shows time series for different values of μ and $\lambda = 0$.

We can see that the highest bond prices are observed for lowest optimism and rigidity, which corresponds to the highest disaster probability. Bond prices decline with belief rigidity, but the effect of climate optimism is non-monotonic. This is because climate optimism affects both the disaster probability and the loss of consumption, which in this case work in opposite directions. The lowest bond price is observed for low climate optimism but high belief rigidity. The difference in bond prices from disaster to non-disaster years follows similar pattern.

Equity returns

Finally, we simulate equity risk premium and equity returns, shown in Figures 7 and 8, respectively. As before, panel (a) shows the average for 1985-2019 as a function of belief rigidity μ and climate optimism λ, panel (b) shows the difference between disaster and non-disaster years in 1985-2019 time period, and panel (c) shows time series for different values of μ and $\lambda = 0$.

We can see that equity risk premium is similar to the AAA corporate bond risk premium, both in

terms of pattern and in terms of magnitude. Highest equity risk premium is observed for cases with lowest optimism and belief rigidity. Similar pattern is observed for differences between disaster and non-disaster years.

Expected return on equity is the sum of risk-free rate and equity risk premium. While risk-free rate is lowest when disaster probability is highest, the risk premium follows the opposite pattern. Since the risk premium in our simulation is substantially smaller in magnitude then the risk-free rate, the risk-free rate effect dominates, leading to lower equity returns in cases when disaster probability is highest. Compared with the risk-free rate, there is more non-linearity with increasing optimism, due to offsetting effect on consumption losses.

Differences between expected returns on equity in disaster and non-disaster years follow an interesting pattern: for very high values of climate optimism or for high belief rigidity, equity returns are slightly higher in disaster years. This is because risk-free rate in these cases does not respond to the disaster but risk premium increases slightly. Essentially, the markets react to disaster year as a surprise. With low belief rigidity and low climate optimism, the risk-free rate in the disaster years is substantially lower due to productivity and GDP losses, and, even though risk premium is higher in these cases, the net effect is negative. In fact, expected return on equity in $\mu = 0$, $\lambda = 0$ case is 4.2 percentage points lower in disaster years than in non-disaster years.

As with corporate bond risk premium, equity risk premium increases over time due to higher disaster frequency, with steeper and more volatile increase occurring when beliefs are less rigid (Figure 7 (c)). However, since the risk-free rate decreases over time, the equity returns actually decline over time in our simulation (Figure 8 (c)) and the decline is more substantial for less rigid beliefs.

5 Application to the Literature

The literature on the response of financial markets to climate shocks is growing rapidly. We group it into studies of fixed income instruments and of equity markets and focus on the studies that address pricing, rather than flows, of assets.

5.1 Literature on Asset Prices and Physical Climate Risks

On the fixed income side, we model U.S. government bond yields as well as corporate bond spreads. Gupta et al. (2018) show the effect of generally defined rare disasters on the return volatility of U.S. long-term government bonds over the last 100 years that we can use as a benchmark. On the corporate debt side, most studies are focused on the transition risks (risks associated with climate mitigation policies, preferences, or technologies) with only a few studies investigating the effects of climate-related disasters. Acharya et al. (2022) investigate the effects of heat stress and find significantly higher yield effects of heat events on below-investment grade bonds relative to

investment-grade bonds, which would be consistent with our model. However, they do not find effects for other climate-related events. Javadi and Al Masum (2021) find that banks that lend in the areas with high climate risks charge higher loan spreads and face higher cost of funding themselves. This suggests that banks pay higher risk premiums on their wholesale funding in these cases.

A number of recent papers address the pricing of climate risks and their effects on the lending amount in syndicated bank lending, including Degryse et al. (2021); Ehlers et al. (2022); Javadi and Al Masum (2021); Kacperczyk and Peydró (2021); Mueller and Sfrappini (2021); Reghezza et al. (2021). We acknowledge the difference between bank lending and the bond market, but include these papers, when they address physical climate risks, into our fixed income analysis for completeness. Mallucci (2022) and Klomp (2017) look at the effects of climate risks on the pricing of sovereign debt (as well as the sovereign's access to the global capital market). While our model is calibrated to the U.S., we still include these paper into our analysis.

The literature on the pricing of physical climate risks in equity markets focuses on the impact of uncertainty and volatility generated by climate-related weather events. Kruttli et al. (2023) highlight that the impact of hurricanes on firms' stock returns occurs through the increase in the implied volatility of the stock options of firms whose establishments fall in the hurricane's landfall region. Huynh et al. (2020) provide evidence for a higher implied cost of equity capital for firms located in regions affected by severe drought, with a stronger effect for firms with higher local institutional holdings. While Bansal et al. (2019) do not focus on disasters, they show that long-run temperature fluctuations carry a positive risk premium in equity prices, while high-frequency temperature fluctuations have an insignificant effect on equity valuations. Krueger et al. (2020) show that institutional investors pay attention to climate risks, although they believe some equity valuations do not yet fully reflect these risks. Alok et al. (2020b) show that local money managers overreact to disasters causing an increase in the cost of capital in affected areas.

5.2 Empirical Findings in the Context of our Model

We can evaluate the findings in these papers in the context of our model simulation. For example, Kruttli et al. (2023) find positive abnormal stock returns following hurricane Sandy. We do not have a measure of abnormal stock returns, but we know it is likely to correspond to the equity premium. Our model does predict higher equity premia in disaster years (Figure 7). Quantitatively, the authors find a range of abnormal returns from 1.9% to 6.0%, which given an average equity returns in our data of 8% would correspond to disaster/no-disaster difference of 0.0015 to 0.0048. Reading from Figure 7 (b), these results are consistent with climate optimism ranging from 0.5 to 0.9 with Bayesian beliefs or from 0 to 0.9 with somewhat rigid beliefs ($\mu < 0.4$), but are not consistent with high belief rigidity.

Acharya et al. (2022) find a positive effect of heat stress on excess equity returns. While heat stress is a continuous measure and cannot be directly mapped to disasters, we know that it is

positively correlated with the disaster arrival rate. Looking at our results on the differences in equity returns for disasters and non-disaster years (Figure 8 (b)), we can see that positive excess returns in disaster years are consistent with either high belief rigidity and low climate optimism or with very high climate optimism. However, the authors only find this effect after 2012, indicating a possible change in belief formation. No effect prior to 2012 is consistent with somewhat lower climate optimism or lower belief rigidity. This is somewhat surprising, we would expect belief rigidity and climate optimism lowering over time.[7]

Acharya et al. (2022) also consider the effect of heat stress on bond pricing. They find higher bond yields and spreads in response to higher heat stress. The effects are negligible for investment grade bonds, but sizeable for below-grade corporate and municipal bonds. This is consistent with our model for all sets of parameters. However, to compare the magnitudes of the effects we would first have to translate their measure of heat stress to disaster probability.

For risky sovereign bonds Mallucci (2022) does not find the default risk related to hurricanes having a sizeable effect on the bond spreads. If we map risky sovereign bonds to B-rated bonds in our data, we can see that zero effect is consistent with climate optimism above 0.9 (reading from Figure 5 (b)) for any level of belief rigidity.

Overall, this analysis shows that most quantitative empirical findings can be mapped into our simulated asset price responses to climate disasters, which allows for deeper understanding of climate belief formation in various asset markets.

6 Summary and conclusions

We argue that belief formation is key to properly benchmarking empirical findings regarding the response of asset prices to climate shocks. We illustrate how such benchmark can be achieved by adapting Gabaix (2012) model in which we allow for time-varying beliefs that also differ in their degree of climate optimism and their rigidity.

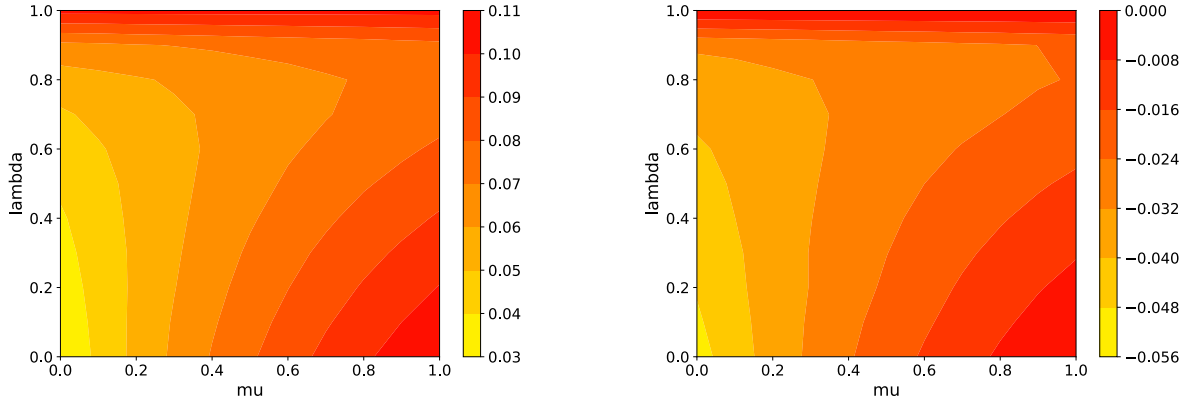
Simulating the model to the time period in which climate-related disaster frequency increased over time, 1984-2019, we show that both belief rigidity and climate optimism are important determinants of asset price response to climate shocks. The effects of these belief parameters on asset price moments is complex and non-monotonic.

There is no consensus in empirical literature with respect to the response of asset prices to climate shocks Campiglio et al. (2023), however our framework allows for interpretation of the findings in the context of climate beliefs.

[7] Of course, zero effect is also consistent with lack of climate risk pricing (outside of our model). To distinguish this from actual climate optimism, one would have to also consider the pricing of transition risks, which are high for the SSSP1 scenario of climate optimism.

(a) Average for 1985-2019

(b) Disaster Year – No Disaster Year



(c) Time Series with $\lambda = 0$

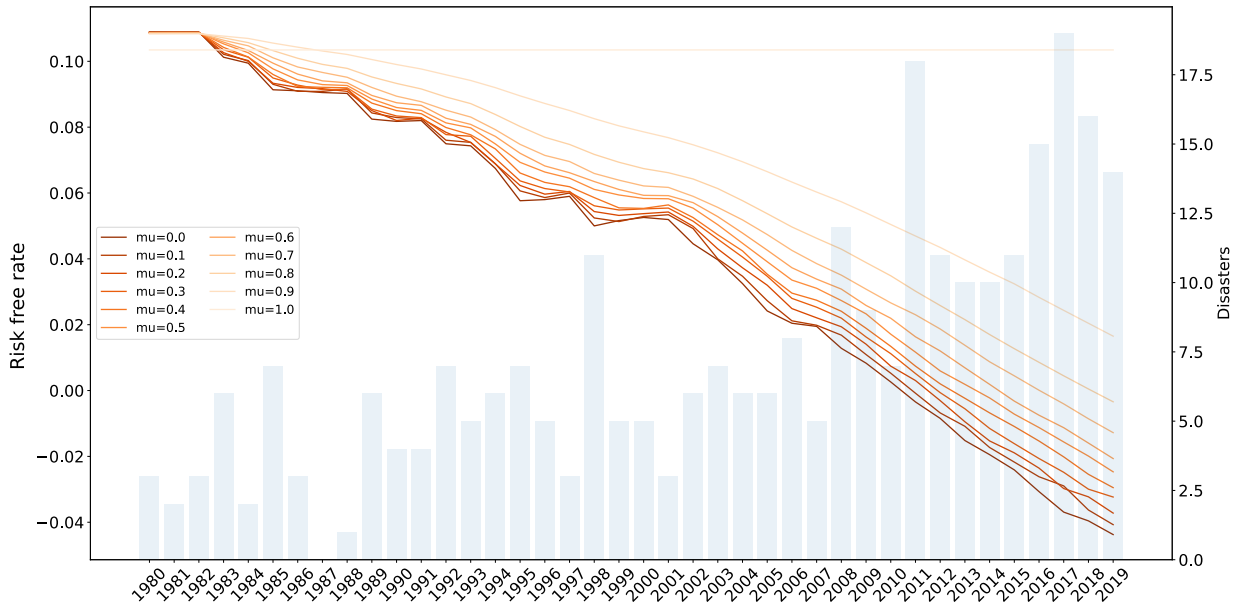
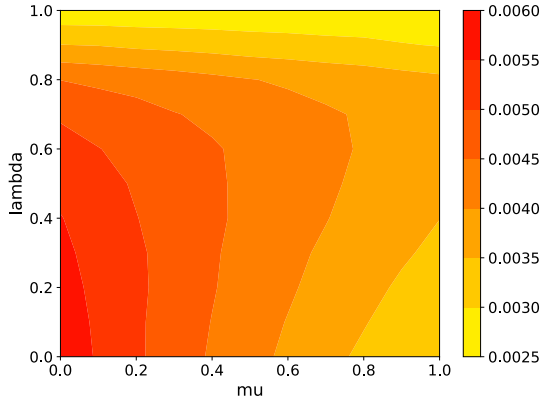


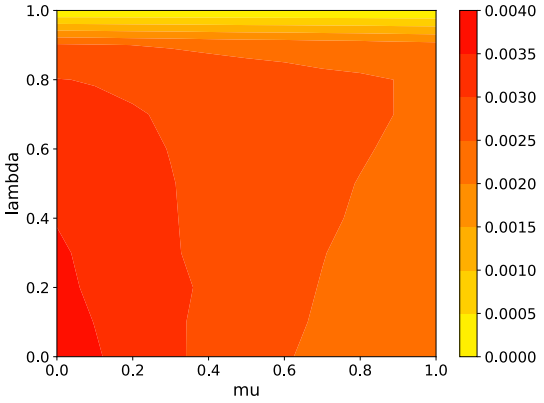
Figure 4: Risk-free rate

Notes: Risk-free rate is computed as in equation 5. Simulation parameters are in Table 1.

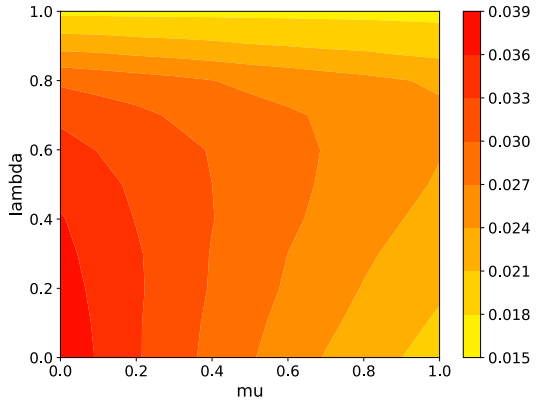
(a) AAA bond, Average for 1985-2019



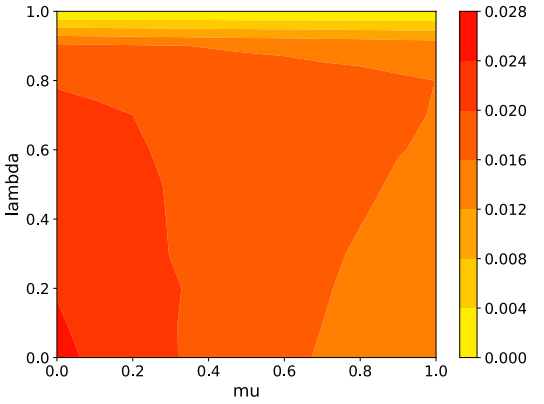
(b) AAA bond, Disaster Year – No Disaster Year



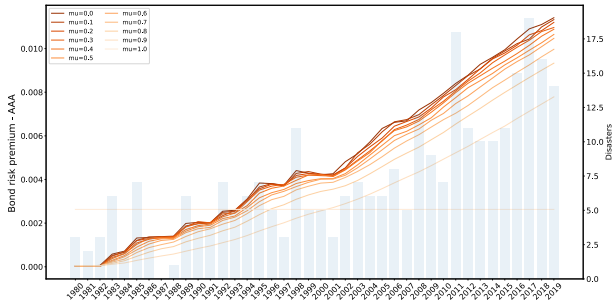
(c) B bond, Average for 1985-2019



(d) B bond, Disaster Year – No Disaster Year



(e) Time Series of AAA bond with $\lambda = 0$



(f) Time Series of B bond with $\lambda = 0$

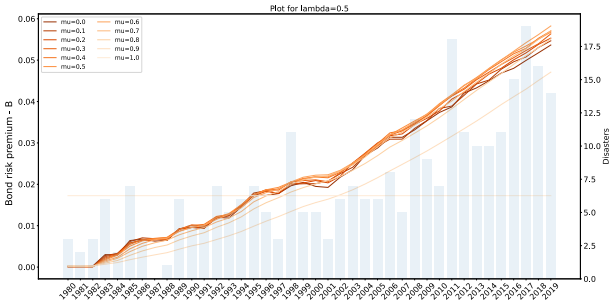
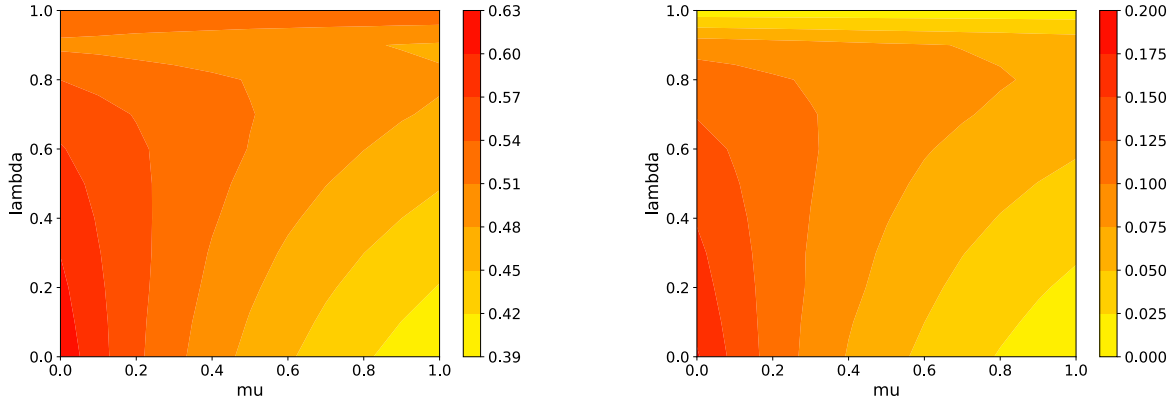


Figure 5: Bond risk premium

Notes: Corporate bond risk premium is computed as in equation 12. Simulation parameters are in Table 1.

(a) Average for 1985-2019

(b) Disaster Year – No Disaster Year



(c) Time Series with $\lambda = 0$

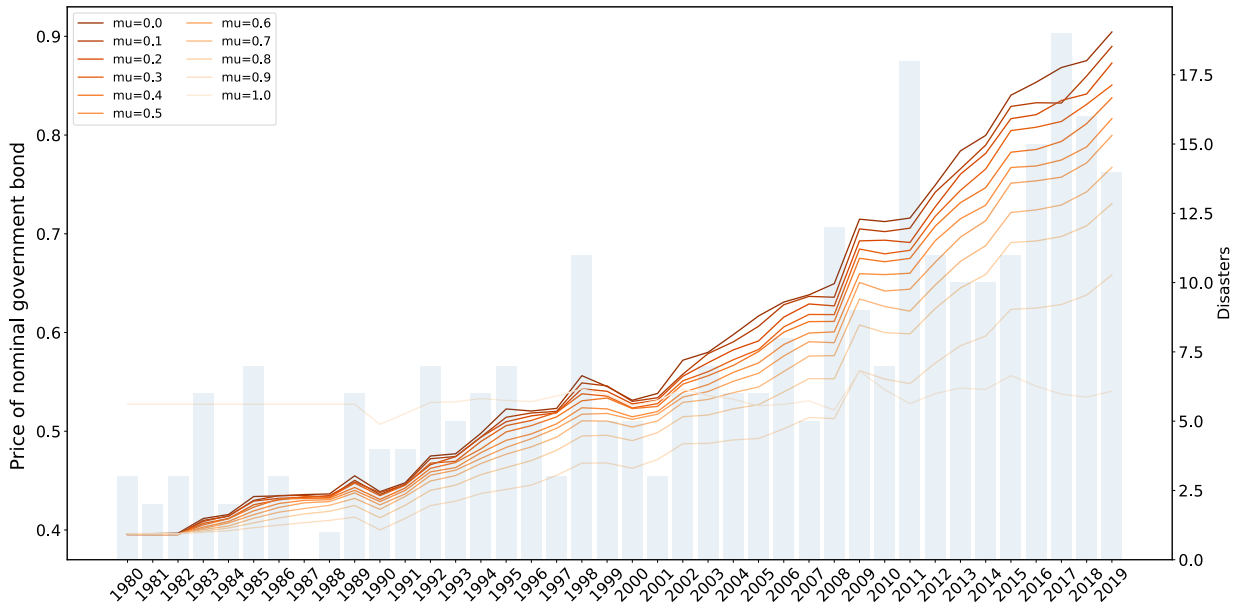
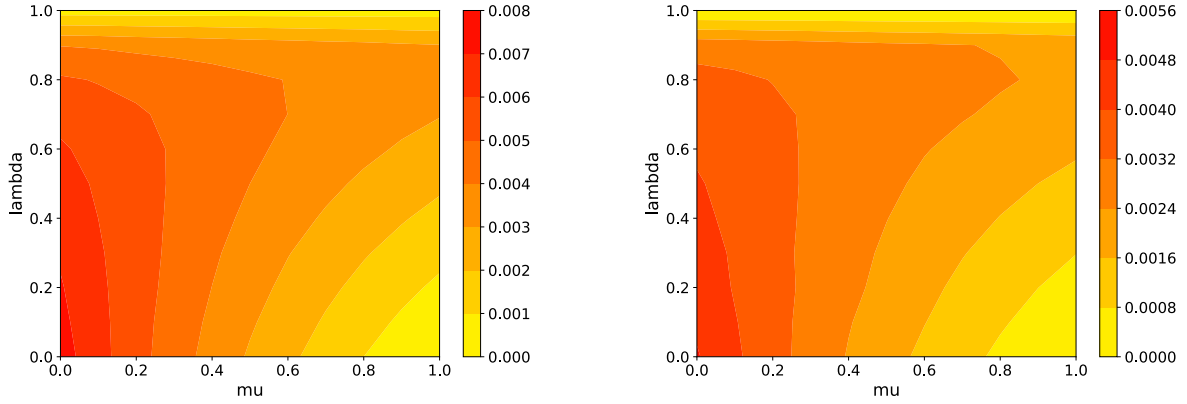


Figure 6: Nominal price of 5-year government zero coupon bond

Notes: Government bond price is derived in equation 9. Simulation parameters are in Table 1.

(a) Average for 1985-2019

(b) Disaster Year – No Disaster Year



(c) Time Series with $\lambda = 0$

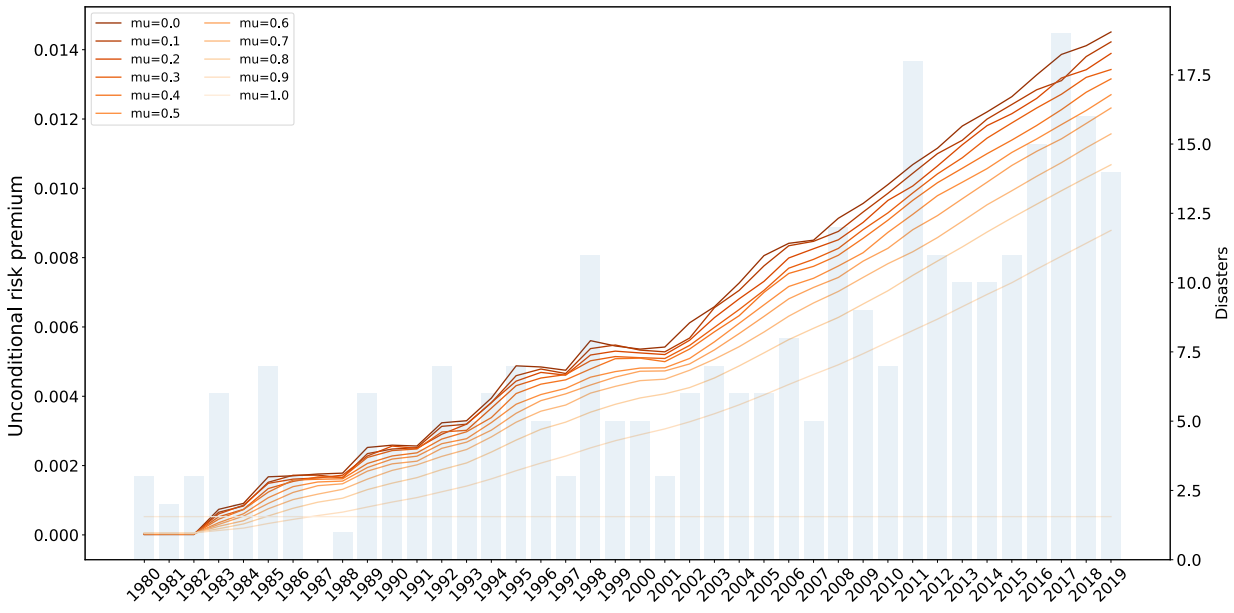
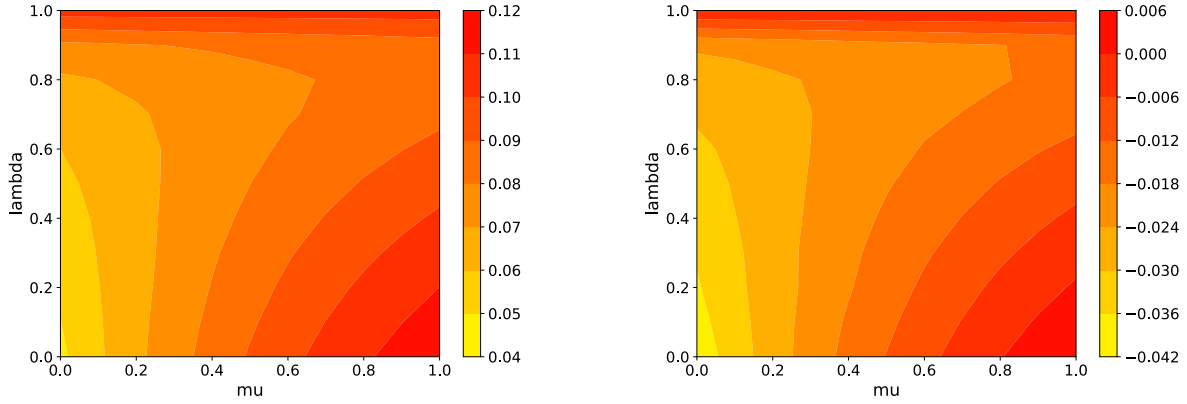


Figure 7: Equity Risk Premium

Notes: Equity risk premium is derived in equation 7. Simulation parameters are in Table 1.

(a) Average for 1985-2019

(b) Disaster Year – No Disaster Year



(c) Time Series with $\lambda = 0$

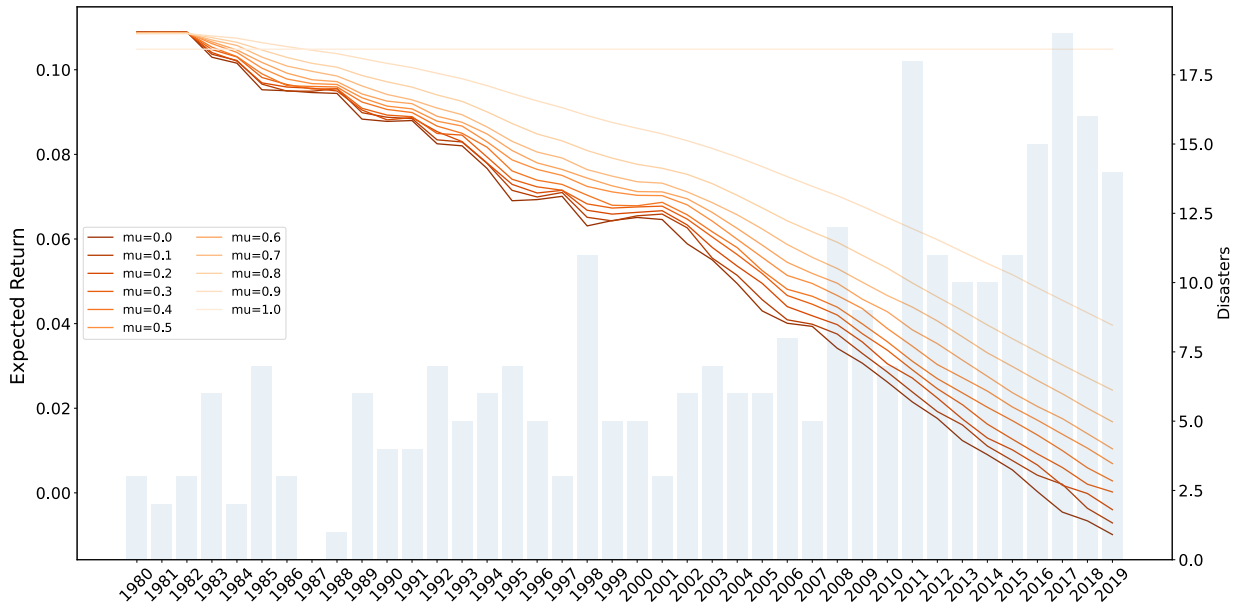


Figure 8: Expected Return on Equity

Notes: Expected equity returns are derived in equation 6. Simulation parameters are in Table 1.

References

Acharya, Viral V, Timothy Johnson, Suresh Sundaresan, and Tuomas Tomunen, "Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress," September 2022.

Alok, Shashwat, Nitin Kumar, and Russ Wermers, "Do fund managers misestimate climatic disaster risk," *The Review of Financial Studies*, 2020, *33* (3), 1146–1183.

_ , _ , and _ , "Do Fund Managers Misestimate Climatic Disaster Risk," *The Review of Financial Studies*, 02 2020, *33* (3), 1146–1183.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, "Climate change risk," *Federal Reserve Bank of San Francisco Working Paper*, 2019.

Barnett, Michael, William Brock, and Lars Peter Hansen, "Pricing Uncertainty Induced by Climate Change," *The Review of Financial Studies*, 02 2020, *33* (3), 1024–1066.

Bodenstein, Martin and Mikaël Scaramucci, "On the GDP Effects of Severe Physical Hazards," 2024.

Campiglio, Emanuele, Louis Daumas, Pierre Monnin, and Adrian von Jagow, "Climate-related risks in financial assets," *Journal of Economic Surveys*, 2023, *37* (3), 950–992.

Degryse, Hans, Roman Goncharenko, Carola Theunisz, and Tamas Vadasz, "When Green Meets Green," Centre for Economic Policy Research Discussion Paper DP16536 2021.

Ehlers, Torsten, Frank Packer, and Kathrin de Greiff, "The pricing of carbon risk in syndicated loans: Which risks are priced and why?," *Journal of Banking and Finance*, 2022, *136*, 106180.

Gabaix, Xavier, "Variable Rare Disasters: A Tractable Theory of Ten Puzzles in Macro-finance," *American Economic Review*, May 2008, *98* (2), 64–67.

_ , "Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance," *The Quarterly journal of economics*, 2012, *127* (2), 645–700.

Gupta, Rangan, Tahir Suleman, and Mark E. Wohar, "The role of time-varying rare disaster risks in predicting bond returns and volatility," *Review of Financial Economics*, November 2018, *37* (3), 327–340.

Hale, Galina, "Climate Disasters and Exchange Rates: Are Beliefs Keeping up with Climate Change?," *IMF Economic Review*, 2024, *72*, 253–91.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, "Climate risks and market efficiency," *Journal of econometrics*, 2019, *208* (1), 265–281.

Huynh, Thanh D, Thu Ha Nguyen, and Cameron Truong, "Climate risk: The price of drought," *Journal of Corporate Finance*, 2020, *65*, 101750.

Javadi, Siamak and Abdullah Al Masum, "The impact of climate change on the cost of bank loans," *Journal of Corporate Finance*, 2021, *69*, 102019.

Kacperczyk, Marcin and José Luis Peydró, "Carbon Emissions and the Bank-Lending Channel," Center for Economic Policy Research Discussion Paper DP16778 2021.

Klomp, Jeroen, "Flooded with debt," *Journal of International Money and Finance*, 2017, *73*, 93–103.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks, "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*, 02 2020, *33* (3), 1067–1111.

Kruttli, Mathias S, Brigitte Roth Tran, and Sumudu W Watugala, "Pricing Poseidon: Extreme weather uncertainty and firm return dynamics," *Available at SSRN 3284517*, 2023.

Mallucci, Enrico, "Natural Disasters, Climate Change, and Sovereign Risk," *Journal of International Economics*, 2022, *139*, 103672.

Mueller, Isabella and Eleonora Sfrappini, "Climate change-related regulatory risks and Bank lending," 2021.

Painter, Marcus, "An inconvenient cost: The effects of climate change on municipal bonds," *Journal of Financial Economics*, 2020, *135* (2), 468–482.

Reghezza, Alessio, Yener Altunbas, David Marques-Ibanez, Costanza Rodriguez d'Acri, and Martina Spaggiari, "Do Banks Fuel Climate Change?," ECB Working Paper 2021/2550 2021.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, "Firm-level Climate Change Exposure," 2020.

Seneviratne, Sonia I, Xuebin Zhang, Muhammad Adnan, Wafae Badi, Claudine Dereczynski, Alejandro Di Luca, Subimal Ghosh, I Iskander, James Kossin, Sophie Lewis et al., "Weather and climate extreme events in a changing climate (Chapter 11, IPCC)," 2021.

Stott, Peter, "How climate change affects extreme weather events," *Science*, 2016, *352* (6293), 1517–1518.

A Estimation of mean-reversion of climate resilience parameter (ϕ_H)

To estimate ϕ_H, we follow Gabaix (2012). The climate-resilience term H_i represents the resilience of stock i to a climate shock, implying that the stocks doing well during a disaster are safer. Consequently, the price-dividend ratio of any stock is increasing in its resilience as the valuations of such stocks are higher. We assume that H_i follows an AR(1) process such that:

$$H_{i,t} = e^{-\phi_H} H_{i,t-1} + \varepsilon_{i,t}$$

Therefore, to empirically estimate the mean-reversion of H_i, we rely on price-dividend ratio. We use the price-dividend ratio for the S&P 500 (pd). We estimate the following auto-regressive model for 1954-84 and 1985-19 at quarterly frequency:

$$pd_t = \alpha_0 + \alpha_1 pd_{t-1} + \varepsilon_t$$

and

$$\phi_H = -log(\alpha_1)$$