How climate-awake are financial markets?

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Preliminary

Abstract

Climate risks are now acknowledged by policymakers, financial market practitioners, and academics as a potentially material threat to financial markets and financial stability. As physical manifestations of climate change become more apparent, shall we expect massive asset repricing and financial destabilization? The answer to this question crucially depends on whether climate risks are properly 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) to 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 the findings if the risks are fully priced in. 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
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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.

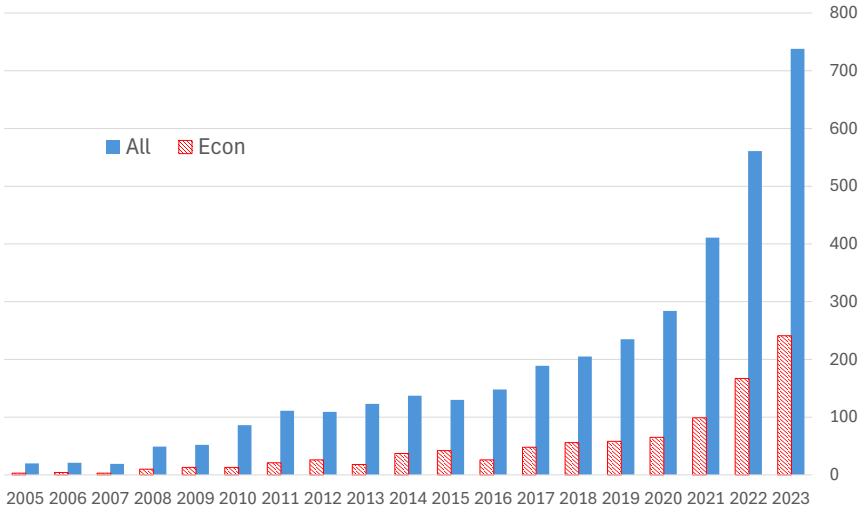


Figure 1: Number of documents containing "climate" and "finance" in Scopus

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

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

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 perception 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. The model also predicts declining risk-free rate and increasing bond and equity risk-premia over time due to increasing disaster probability. 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 premia are always higher in disaster years, again especially for low climate optimism and low belief rigidity. Risky bonds are more sensitive to belief parameters than AAA bonds.

[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.

[3]Higher Poisson parameter means higher disaster arrival rate as well as higher variance.

There are two ways to interpret empirical papers that find zero or small response of asset prices to physical climate risks. One interpretation is that the markets simply do not pay attention to these risks, which is a deviation from rationality. In the context of our model, these negative findings would be 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, we are able to offer the set of parameters that are consistent with the response. [This part is still preliminary]

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 both methodological, in terms of modeling asset prices in the presence of non-i.i.d. climate shocks and explicit belief formation, and as meta-analysis of the empirical literature on the response of financial market to climate shocks. We discuss the literature in Section 5.

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.

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.

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

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:

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

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_{it}^e can be expressed as

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

which gives us the unconditional equity risk premium $q_{it} = r_{it}^e - r_t^f$:

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

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

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

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:

$$y_t^G(M) = -\frac{\ln Z_t(M)}{M} \tag{10}$$

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

$$y_{lt}(M) = y_t^G(M) + PD_l + p_t B_t^{-\gamma} (1 - F_{lt}), \tag{11}$$

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

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

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 be 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.[6]

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.

4.1 Simulation set-up

To simulate the model, we collect additional data.

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

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

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

[6]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 of mean reversion in both periods, higher level of jump mean-reversion in calibration period and lower level in simulation period. We are unable to match the data in our calibration period with Gabaix (2012) calibration.

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)		0.7505	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

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 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 also update values of disaster-related losses to better match the average risk-free rate and return on equity in the simulation period to $B = 0.83$ (lower consumption losses) and $F = 0.905$ (higher productivity and dividend losses). The rest of the parameters are as in calibration.

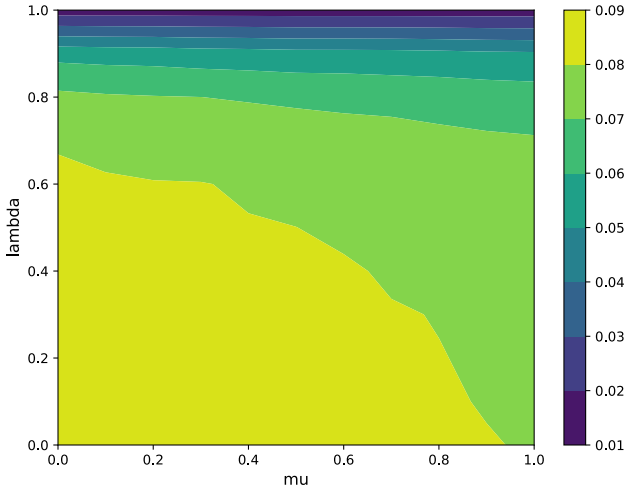


Figure 2: Probability of disaster

4.2 Simulation results

We present our simulation results in two ways: as time series for specific values of belief parameters λ and 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 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 ($\theta_0 = \Gamma(a0, 1)$ where $a0 = 0.0666$ is the pre-sample disaster arrival rate estimated in Hale (2024)). With Bayesian updating the subjective probability increases over time with higher increase for 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.

We begin with risk-free rate shown in Figures 4(a) and 5. We can see that it is increasing in

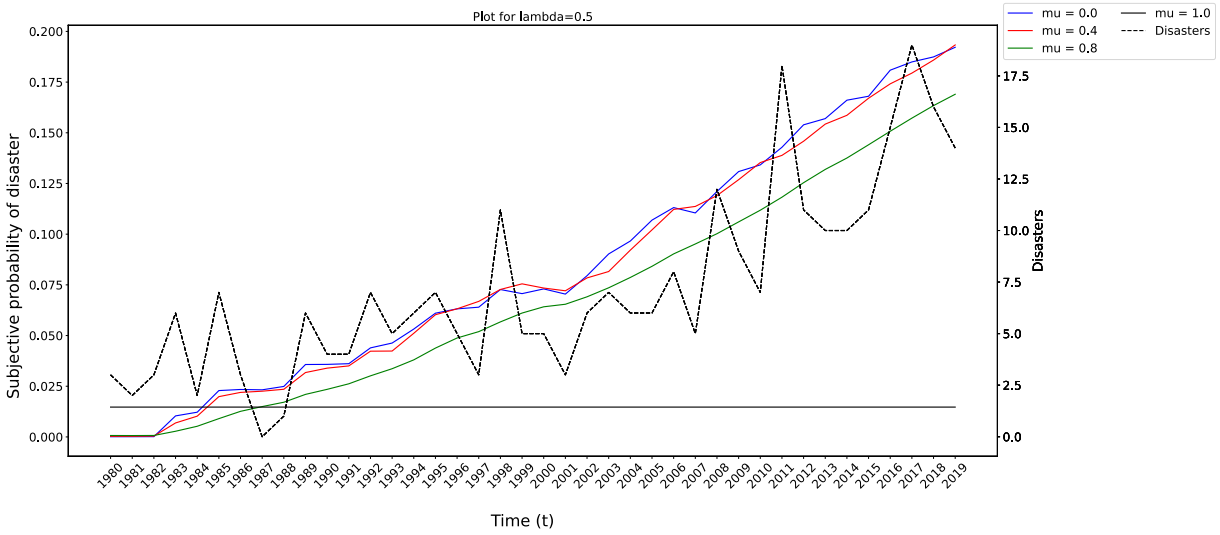


Figure 3: Probability of disaster

climate optimism (because it is negatively associated with disaster probability), but for low values of λ it is also increasing with belief rigidity. We observe from the time series that the more Bayesian (less rigid) are the beliefs, the more volatile the risk-free rate is in response to observed disasters. 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. Figure 4(b) shows the difference between disaster years and no-disaster years. Generally, disaster year risk-free rate is lower than no-disaster year. 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 disaster probability.

Turning to risky returns, we simulate bond risk premia for AAA-rated and B-rated corporate bonds. The period-average simulated values are plotted in Figure 6, the differences between disaster and no-disaster years in Figure 7, and the time series in Figures 8 and 9. We can see that for corporate bonds, bond risk premium mirrors the disaster probability, which is highest for low climate optimism and low belief rigidity. However, the role of belief rigidity is more pronounced for any $\lambda < 0.7$. Comparing values for AAA and B-rated bonds, we can see that the impact of belief parameters is substantially larger for risky bonds than for the risk-free ones. Focusing on the difference between disaster and no-disaster years, we can see that these differences are highest for risky bonds, especially when climate optimism is low, with some non-monotonic effects observed at high values of belief rigidity.

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 10 shows period average as well as the difference between disaster and no-disaster

years, and figure 11 shows the time-series for the 5-year government bond prices. We can see that when climate optimism is high, the higher the optimism the higher are the government bond prices. The lowest prices are for climate optimism around 0.9 and high belief rigidity. For lower levels of climate optimism, government bond prices increase slightly especially as belief rigidity declines. In disaster years, government bond prices are higher if climate optimism and belief rigidity are both low, i.e. if disaster probability is high.

Finally, we simulate equity returns and equity premium. Figure 12 shows the period average equity returns as well as the difference between the disaster and no-disaster years, and figure 13 shows the time series for expected equity returns. We can see that the pattern is similar to the risk-free rate with both average returns and the difference between disaster and non-disaster years increasing with climate optimism and belief rigidity.

Figure 14 shows the period average as well as the difference between the disaster and no-disaster years for equity premium and Figure 15 shows time series. We can see that equity premium generally follows the pattern of disaster risk on average — it is highes when both climate optimism and belief rigidity are low. In terms of dynamics, we can see that with rigid beliefs our model does not produce almost any equity risk premium. However, for Bayesian agents equity premium increases over time as disaster probability grows.

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.

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 that 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. 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. 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. (2020) show that local money managers overreact to disasters causing an increase in the cost of capital in affected areas.

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. 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, or, reading from Figure 14(b), climate optimism $\lambda < 0.9$ for the low end of the range, and either climate optimism between 0.7 and 0.9 with low belief rigidity or low climate optimism with high belief rigidity for the high end of the range. 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 map to disasters, we know that it is positively correlated with the disaster arrival rate. Positive effect on returns is consistent with low climate optimism and belief rigidity. However, the authors only find this effect after 2012, indicating a possible change in belief formation. No effect prior to 2012 is consistent with high climate optimism or complete belief rigidity. This is not a surprising results — many studies find that effects of climate risks on asset prices are more pronounced following COP12 meeting in Paris in 2015.[7]

Acharya et al. (2022) also consider the effect of heat stress on bond yields. 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 also consistent with low levels of climate optimism and belief rigidity. For risky sovereign bonds Mallucci (2022) does not find the default risk related to hurricanes having a sizeable effect on the bond spreads. If

[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.

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 7), or complete belief rigidity.

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 climate optimism is an important determinant of asset price response to climate shocks. In terms of belief rigidity, we find that extreme belief rigidity, no update at all, implies essentially no response of asset prices to climate shocks. However, even a small reduction in rigidity produces asset price response that is then sensitive more to climate optimism than belief rigidity.

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. For example, a number of papers only find a significant effect in the years following Paris Climate Accord (2015), which is consistent with beliefs becoming more rigid or less optimistic, or both, following COP21.

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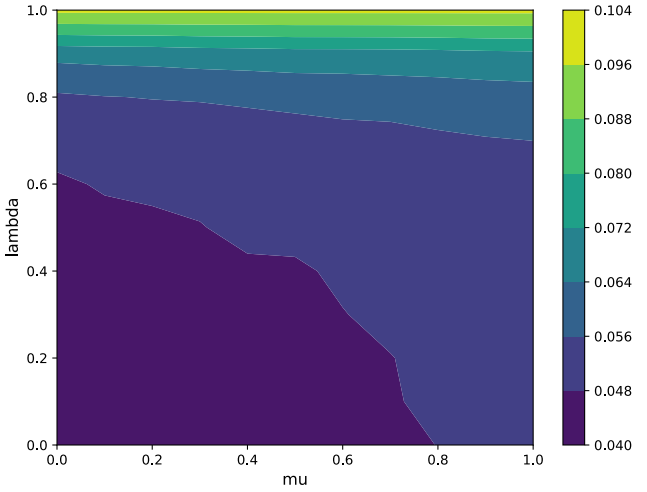
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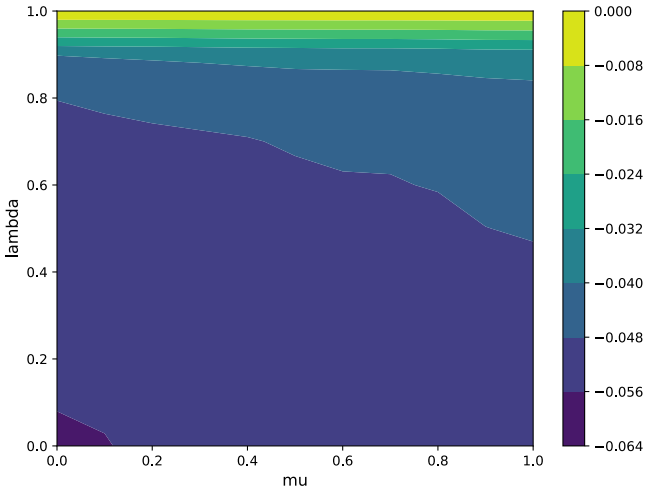
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(a) Average for 1985-2019



(b) Disaster Year - No Disaster Year

Figure 4: Risk-free rate

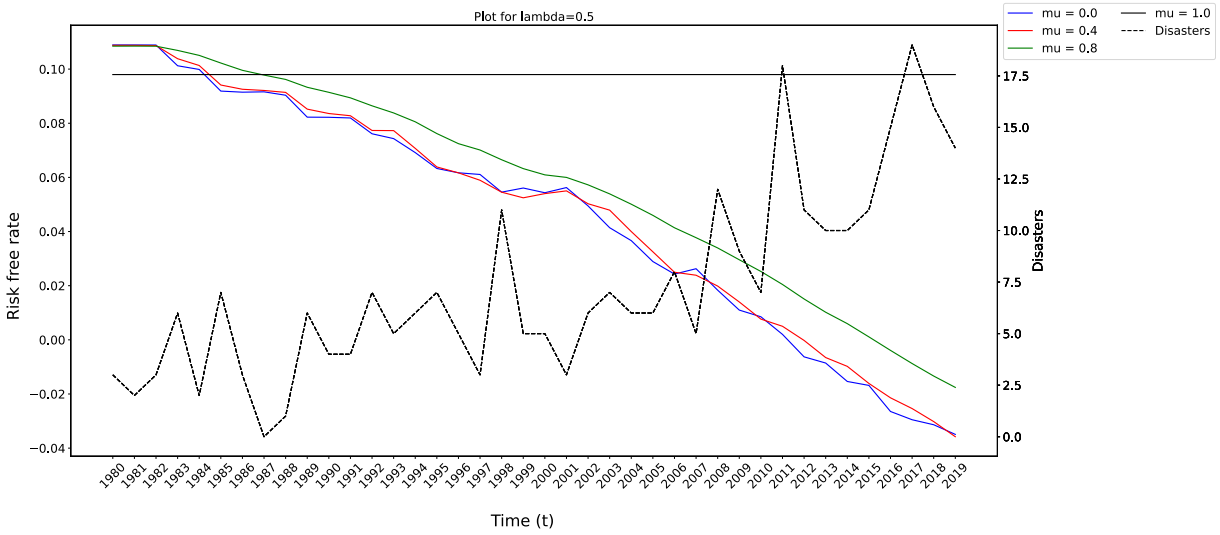
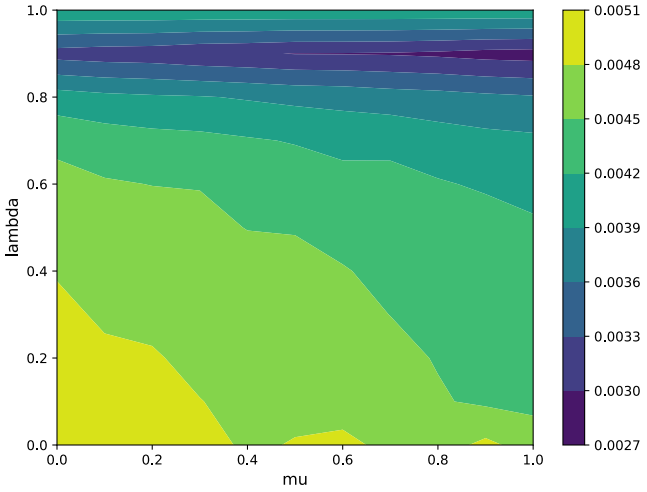
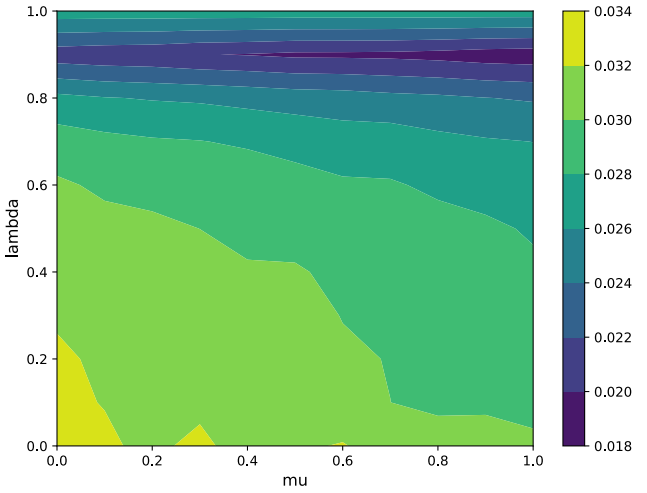


Figure 5: Risk free rate

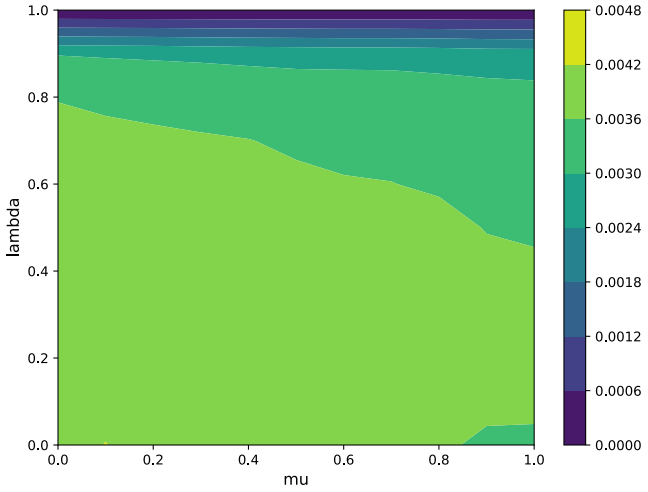


(a) AAA bond

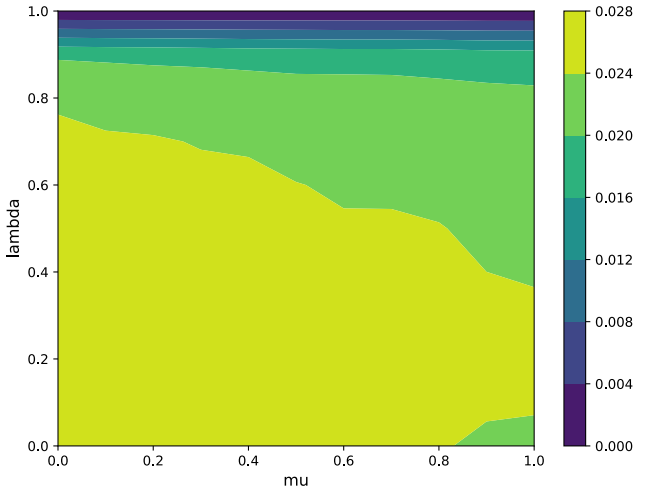


(b) B bond

Figure 6: Bond Risk Premium (1985-2019 average)



(a) AAA bond



(b) B bond

Figure 7: Bond Risk Premium (Disaster Year - No Disaster Year)

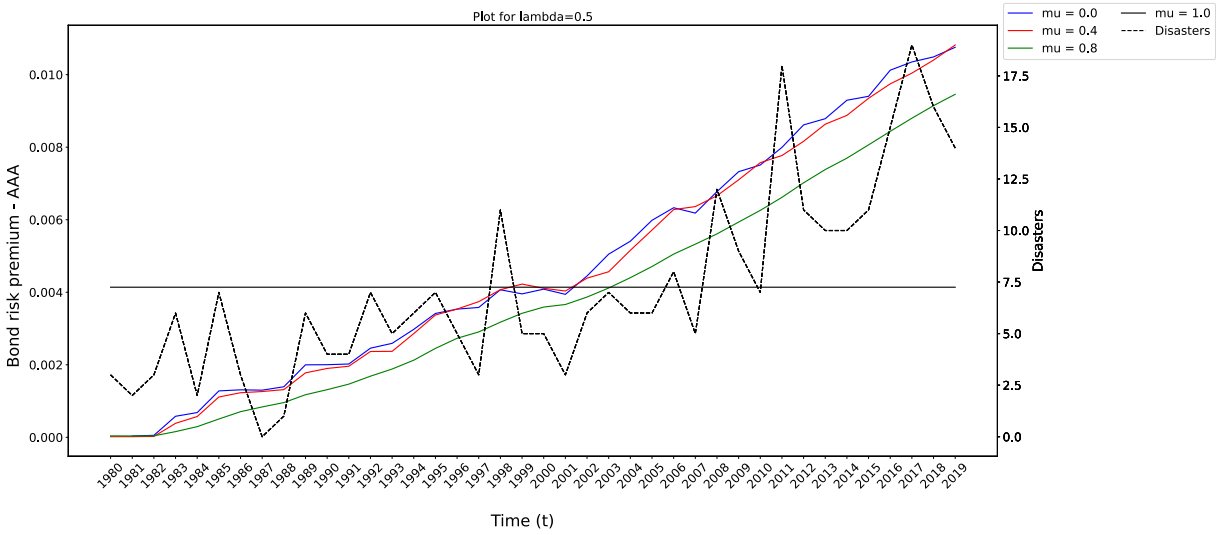


Figure 8: AAA-rated bond risk premium

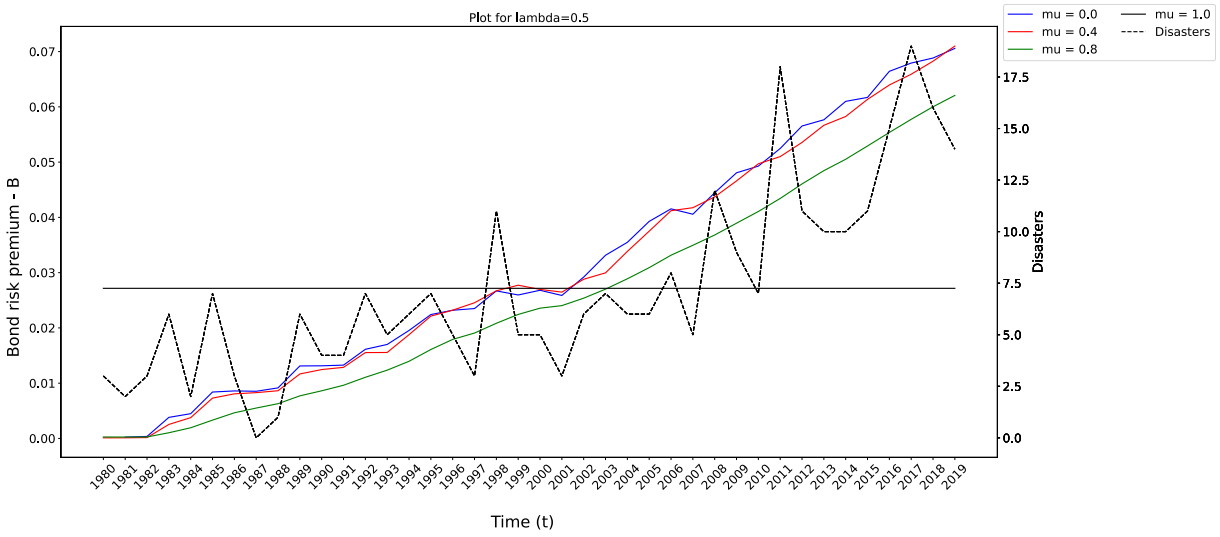
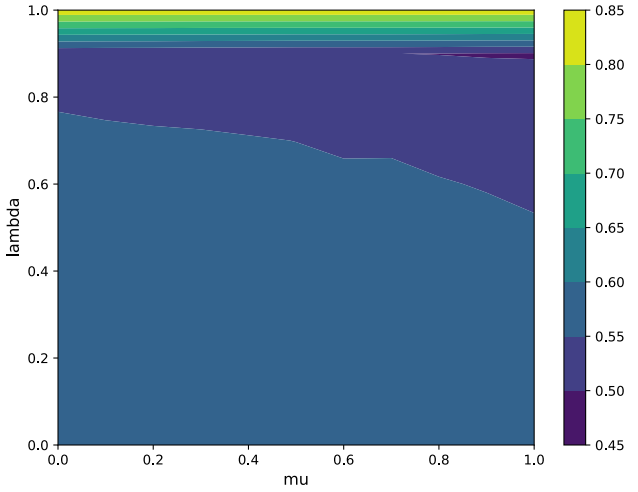
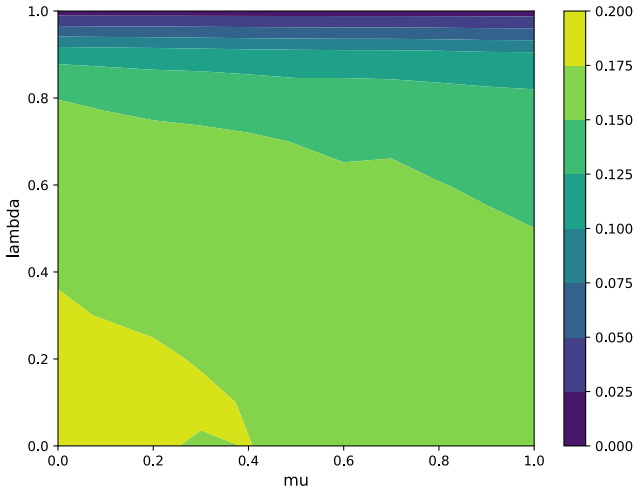


Figure 9: B-rated bond risk premium



(a) 1985-2019 average



(b) Disaster - No Disaster

Figure 10: Nominal price of government zero coupon bond (Maturity - 5 years)

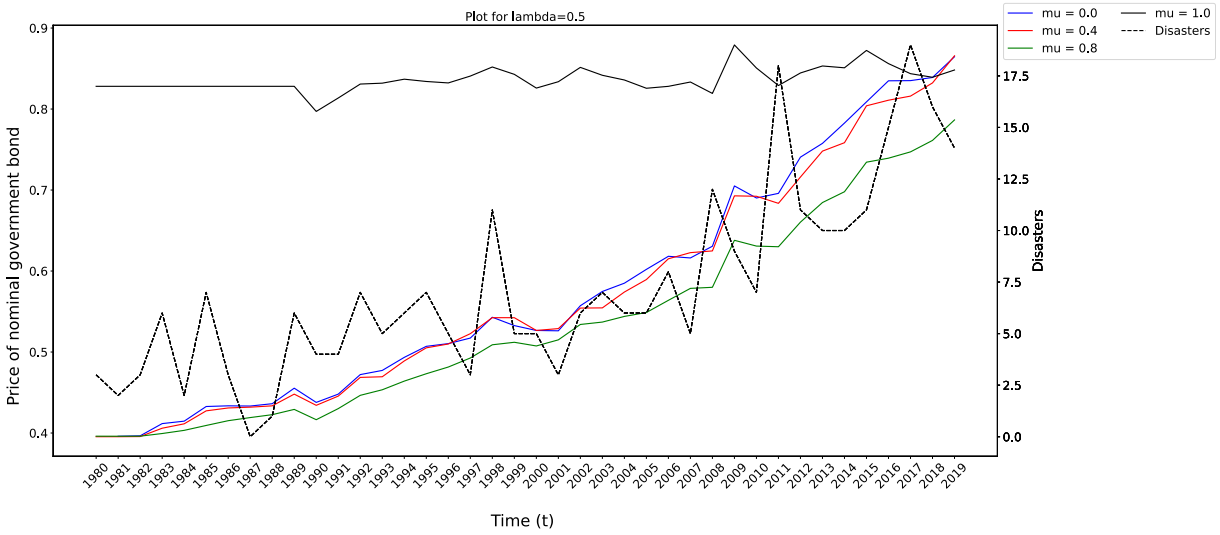
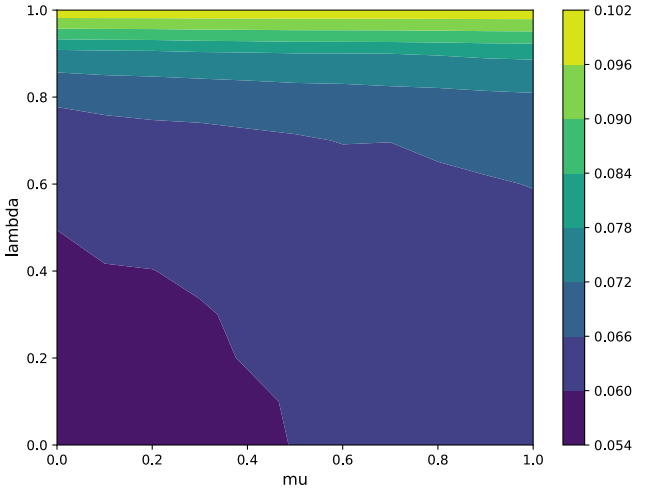
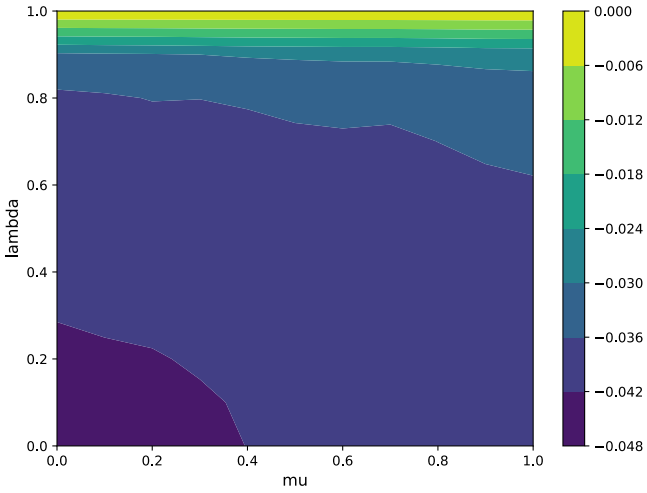


Figure 11: 5-year Government Bond Price



(a) 1985-2019 average



(b) Disaster Year - No Disaster Year

Figure 12: Equity Expected Returns

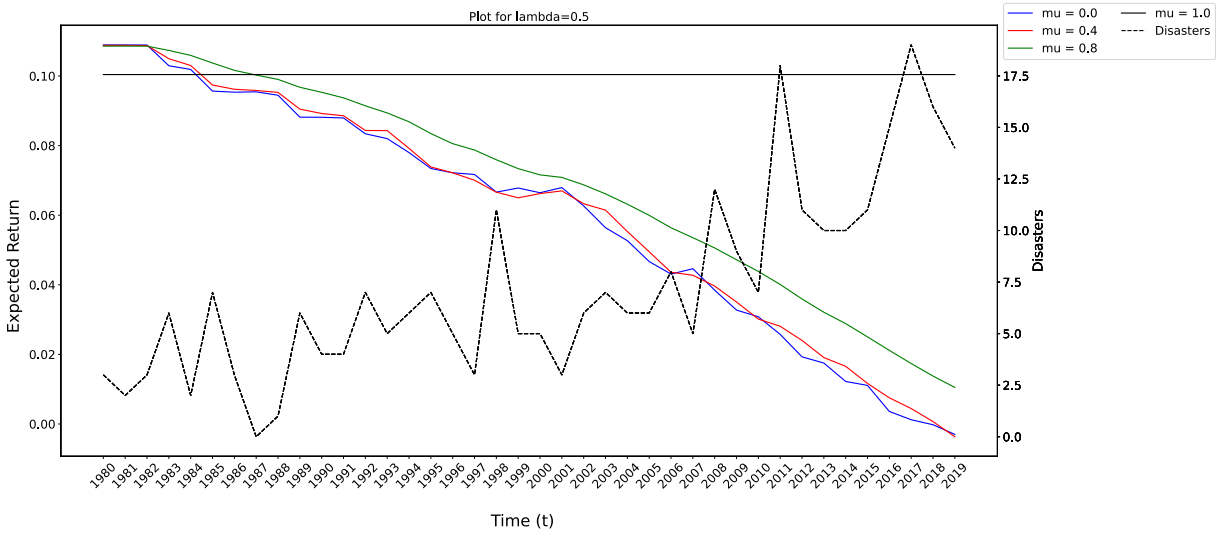
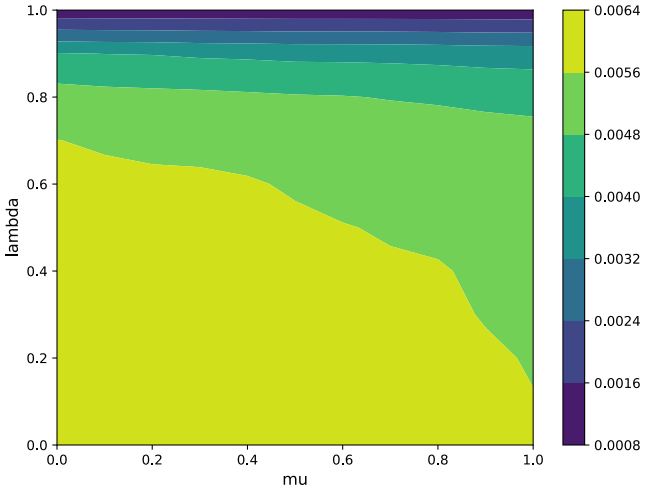
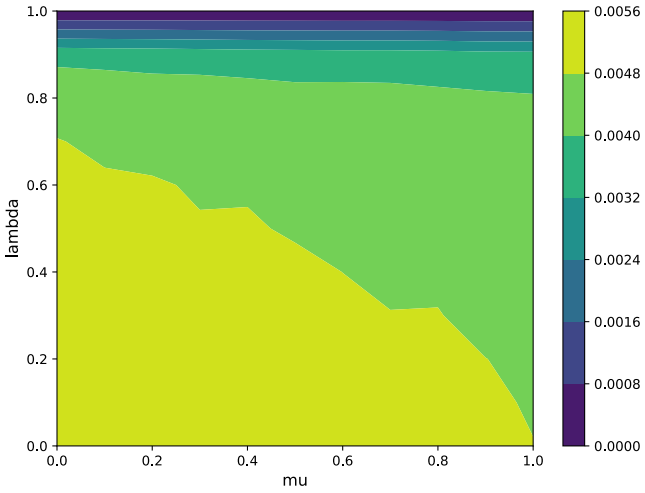


Figure 13: Equity Expected Returns



(a) 1985-2019 average



(b) Disaster Year - No Disaster Year

Figure 14: Equity Risk Premium

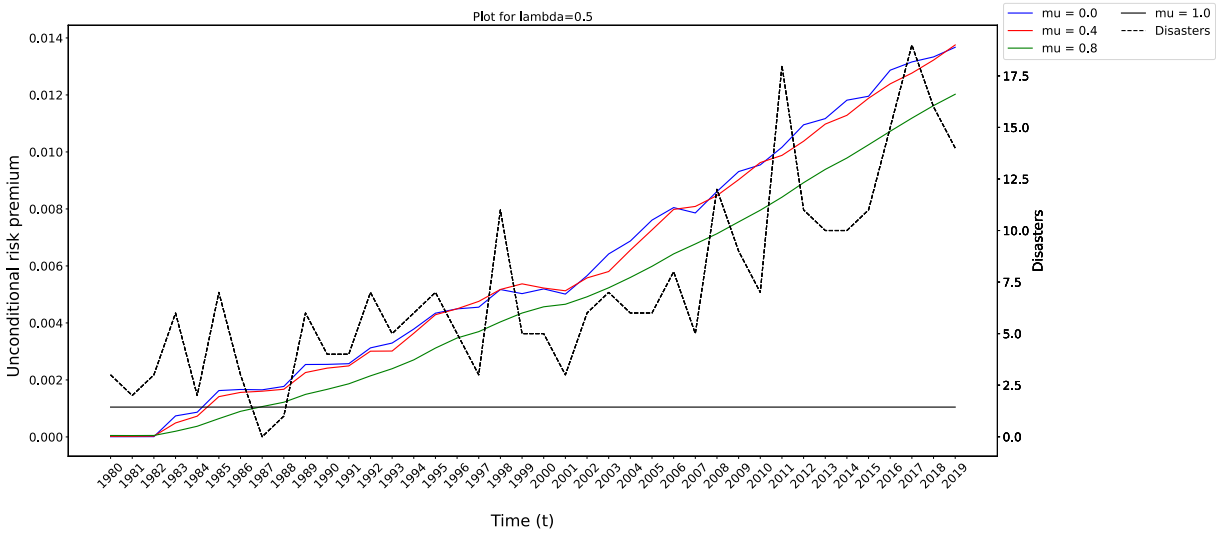


Figure 15: Equity risk premium

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

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