Adaptation Under Evolving Climate Uncertainty

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Abstract

Adaptation is an increasingly attractive option for addressing economic damages from climate change, which are subject to significant climate uncertainty. However, uncertainty in climate damages is expected to change over time as the pace of decline in emissions is observed and geophysical models are improved. I leverage an ensemble of climate models to quantify the current extent and expected path of uncertainty. I incorporate the results into a real options model to quantify how raising the speed of uncertainty resolution increases welfare while reducing the necessary level of investment.

1 Introduction

Though climate change is a real and salient threat, there remains great uncertainty around its projected impacts. For a start, there is uncertainty regarding the path of atmospheric greenhouse gas concentrations, as embodied in the various scenarios that researchers consider. An additional layer of uncertainty comes from our imperfect understanding of climatic processes, as reflected in variations in the projected impact of any given scenario across different climate models. Uncertainty in climate impacts in turn generates uncertainty regarding the optimal level of investment in climate adaptation. Because investments in adaptation must be made before climate impacts are realized, this raises the potential for costly mismatches.

Accounting for uncertainty around climate projections is therefore crucial for policymakers seeking to engage in climate adaptation. Consider the classic example of a seawall that guards against sea level rise. A proposal to construct a seawall in New York City that would protect against a sea level rise of 1.8 meters cost 119 billion dollars(Barnard, 2020). Should the realized sea level rise be greater, the effectiveness of the seawall will be limited; if instead the sea level rise is far below expectations, a smaller investment would have been sufficient. Given the magnitude of adaptation expenditures, billions of dollars can depend on the degree of uncertainty in available projections.

A good deal of effort goes into measuring the degree of uncertainty associated with current projections of climate damages. Less frequently noted is the point that this degree of uncertainty can be expected to change over time. A policymaker considering the uncertainty around end-of-century climate damages is aware that every year that passes will provide information about the amount of carbon emitted that narrows the range of possible carbon scenarios. Climate models may also come to greater consensus over time as research continues. Because of this partial resolution of uncertainty over time, the policymaker today cares not only about the level today but the expected level of uncertainty at various points in the future.

A rich literature on real options reaching back to Arrow and Fisher (1974) informs us that decreasing uncertainty may incentivize delays in irreversible investments under uncertainty. Returning to the example of the seawall, it may be preferable to delay the investment if the 2100 sea level rise will be known with greater certainty in 10 years. Waiting for the resolution of uncertainty reduces the likelihood of overshooting the necessary investment, even if it conflicts with the general preference for spreading out large-scale expenditures over time.

Optimal adaptation therefore requires a tradeoff between consumption smoothing and the benefits of delaying investment. To formalize this intuition, I adapt a real options pricing model to link climate uncertainty with climate adaptation investment decisions. The policymaker in this framework must decide how much to invest in climate adaptation to prepare for uncertain climate change while anticipating updates to the variance around expected damages each period. I find a closed-form solution demonstrating the negative relationship between decreases in uncertainty and optimal investment levels.

It should be noted that the problem of optimal climate adaptation that I present in this paper is tractable because it solves for partial equilibria. With a few notable exceptions, individual nations cannot manage climate risk with mitigation strategies because they cannot unilaterally shift the global path of carbon emissions. Investments in adaptation enable independent reduction of country-specific damages, avoiding the coordination problem of mitigation. The optimal level of investment for a nation therefore can be found by taking the scenarios of global path of carbon emissions as independent of adaptation choices. This also allows for calibration using estimated paths of uncertainty.

Generating policy implications for climate adaptation requires quantification of both the current magnitude of climate uncertainty in economic damages and the the evolution of this magnitude. To estimate the former, I collect an ensemble of climate model outputs for standard carbon scenarios from the current phase of the central climate modeling initiative. Using the damage function from Burke et al. (2015c), I translate these projections of climate realizations into economic damages. Applying a standard climate methodology to the resulting distribution of damages yields estimates of overall climate uncertainty from its components representing uncertainty around climate models and carbon scenarios.

To quantify how this climate uncertainty changes over time, I introduce a new empirical object: the expected uncertainty resolution speed. Defined for each period as the change in the expected uncertainty from the previous period as a proportion of the initial degree of uncertainty faced in the present day, this reflects how fast information is revealed across periods. Because uncertainty resolution speed cannot be estimated directly for overall climate uncertainty, I construct it using the resolution speeds of the component uncertainties weighted by their relative contribution to the initial degree of climate uncertainty.

I estimate the resolution speed of the portion of climate uncertainty attributed to scenarios of carbon concentrations for each decade between 2020 and 2100, using probabilistic projections of carbon concentrations by Rennert et al. (2021). Expected scenario uncertainty in global carbon concentrations decreases nonlinearly, with a rapid decline in the middle of the century. This uncertainty resolution applies to the global scale, and can be treated as exogenous by policymakers for individual countries.

To find evidence for the resolution of uncertainty in climate models, I compare its magnitude in the current phase of the central climate modeling initiative to that of the previous phase. I find no systemic evidence of declining climate model uncertainty over the decade or so between these two phases: while model uncertainty decreases for many nations, it increases for others. While this is contrary to expectations[1], realizations of model uncertainty may increase even as its expectation decreases. Given the limited data, this lack of evidence does not refute the intuition that model uncertainty should resolve over longer time spans with advances in climate science.

To examine the effect of variations in the speed of uncertainty reduction, I instead establish three illustrative paths of climate uncertainty resolution by combining the estimated scenario uncertainty resolution speeds with different assumptions for the path of model uncertainty resolution speeds. I calibrate the framework for these three paths with estimates for a sample of 121 countries expecting negative climate impacts.

Accounting for the evolution of uncertainty increases expected utility while reducing the necessary level of investment; higher climate uncertainty resolution speeds amplifies these effects. Taking Vietnam as an example, the optimal level of investment over the decade spanning 2020-2030 in a scenario where overall climate uncertainty does not decline over time is 4.4% higher than in a scenario where climate models are expected to improve steadily over the rest of the century. Results are similar across the sample of countries; though there is variation, the optimal initial value with steady improvement is on average 3% above that of no improvement.

This paper builds on an active literature around uncertainty and climate change. As noted in by Jensen and Traeger (2024), much of the recent work examines uncertainty in the context of social cost of carbon. Lemoine (2021) and van den Bremer and van der Ploeg (2021) analytically demonstrate the effect of climate uncertainty on the social cost of carbon, while papers by Gillingham et al. (2018), Cai and Lontzek (2019), and Dietz et al. (2021) make use of computationally intensive simulations to

[1] Gillett (2024) suggests the range has decreased for the same scenarios.

explore the effect of both statistical and climate uncertainty on social cost of carbon, general equilibrium. Meanwhile, Hong et al. (2023) explicitly addresses climate uncertainty and learning in optimal adaptation in the context of hurricanes, providing both a framework and quantification for disaster risks. My work similarly focuses on the role of evolving climate uncertainty on adaptation decisions, but accounts for a different dimension of climate damages by focusing on the projected impacts to macroeconomic productivity.

The framework I establish follows in the vein of a series of papers by Guthrie (2019, 2021, 2023) on applying Bayesian decision frameworks for adaptation in localized contexts given changing uncertainty. These works, which offer a real options model as well as more tractable alternatives for studying optimal investments, share a framework with two possible scenarios of climate change for which the policymaker continually updates beliefs. I consider instead the realized value of climate change as a random walk from the initially projected expected value. This allows the use of climate model outputs for quantification.

Empirically, I contribute to measurement of climate uncertainty around climate damages by incorporating advances from climate science. Burke et al. (2015a) highlighted the components of climate uncertainty in estimates of climate impacts, but limitations of climate models at the time prohibited quantification of all of the components. Recent advances now allow for a more complete accounting of climate uncertainty, as demonstrated by Lehner et al. (2020) for temperature projections. Schwarzwald and Lenssen (2022) applies this methodology to estimate the uncertainty in economic impacts for different years in the United States. I build on their approach with an expanded sample of models and countries and further apply it to examine the expected change in end-of-century uncertainty over time.[2] I establish

[2]To be more specific, Schwarzwald and Lenssen (2022) estimate climate uncertainty and its

uncertainty resolution speed as an empirical object to capture this evolution, which in turn allows me to calibrate the framework with different assumptions for model uncertainty. This calibration yields policy implications for the expected path of uncertainty resolution speed.

Just as higher uncertainty resolution speed incentivizes delays to investment, reductions to the speed, such as recent climate science funding cuts in the United States, incentivizes expediting investment. It stands to reason that climate science funding can serve as a lever for hastening the resolution of model uncertainty, and through it overall climate uncertainty. The cost of climate research is magnitudes smaller than that of adaptation; the price of the New York City seawall proposal alone is fifty times the climate research funding disbursed by the National Institute of Health from 2000 to 2022 (Sovacool et al., 2024). The potential reductions in adaptation investment (and thus increases in consumption) that would result from faster uncertainty resolution should be taken seriously in considering future research spending.

The rest of this paper is organized as follows. Section 2 formalizes the intuition with a toy model, then expands it into a generalized framework. The objects of interest that arise from the framework, specifically the degrees of uncertainty and the time paths of uncertainty decline for both emissions and cross-model variation, are quantified in Section 3. Section 4 calibrates the generalized framework with the resulting estimates to explore policy implications. Section 5 concludes.

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components around damages for periods from 2010 to 2100, whereas I examine how uncertainty around damages for the representative year 2100 is expected to change as as we move from present day to the future. I further incorporate probabilities for standard climate scenarios to better capture scenario uncertainty.

2 Framework

Higher climate uncertainty incentivizes greater investment in adaptation due to risk aversion. Because nations have the option to invest over several years, they have some leeway in adjusting the timing and amount of investment each year to reach an eventual target level of investment. If uncertainty is expected to decrease over this time, there is some benefit to delaying investment in the earlier periods. The speed of the decrease in uncertainty will affect the tradeoff between reduced uncertainty and the preference for consumption smoothing. I first demonstrate this intuition with a toy model, which is generalized for calibration.

2.1 Toy Model

Consider a model in which a nation can make adaptation investments in periods 0 and 1 to reduce uncertain damages that will be realized in period 2. The nation will be given information that decreases the uncertainty around the level of damages after period 0, before making the investment decision for period 1. This creates some benefit to delaying investment until period 1, but how much this affects the level of optimal investment in each period depends on how much uncertainty is resolved between the two.

More specifically, assume that climate damage realized in period 2 is represented as the level of income with climate change normalized by the level of income achieved in period 2 in the absence of climate change. This post-climate change income has an expected value of $\bar{w}_{dam}$ in period 0. In each period i that follows, climate signal z_i indicating the incremental deviation from this expected value is drawn from an independent normal distribution. The realized level of income with climate change is then

$$w_{dam} = \bar{w}_{dam} + z_1 + z_2, \text{ where } z_1 \sim N(0, \sigma_1^2) \text{ and } z_2 \sim N(0, \sigma_2^2) \tag{1}$$

Figure 1 outlines the timeline of this model. In period 0, the nation learns $\bar{w}_{dam}, \sigma_1^2$, and σ_2^2 from damage projections. It then earns income w, also normalized by the level of income achieved in period 2 in the absence of climate change, from which it chooses to invest a_0. It derives utility $U(w - a_1)$ from consuming the rest to end the period. Moving to period 1, the nation observes the first signal z_1. It again earns income w, from which it invests a_1 and derives utility $U(w - a_1)$. This leads to the final period, when the second signal z_2 is drawn, determining w_{dam}. Damages are reduced by the cumulative level of investment in adaptation, so the nation consumes $w_{dam} + a_0 + a_1$ at the end of the model.

Figure 1: Toy Model Timeline

Period 0	Period 1	Period 2
1. Learn $\bar{w}_{dam}, \sigma_1^2, \sigma_2^2$	1. Learn z_1	1. Learn z_2
2. Receive income w	2. Receive income w	2. Realize $w_{dam} = \bar{w}_{dam} + z_1 + z_2$
3. Set investment a_0	3. Set investment a_1	3. Receive $\bar{w}_{dam} + a_0 + a_1$
4. Gain $U(w - a_0)$	4. Gain $U(w - a_1)$	4. Gain $U(w_{dam} + a_0 + a_1)$
$E_0[w_{dam}] = \bar{w}_{dam}$	$E_1[w_{dam}\|z_1] = \bar{w}_{dam} + z_1$	$E_2[w_{dam}\|z_1, z_2] = \bar{w}_{dam} + z_1 + z_2$
$V_0[w_{dam}] = \sigma_1^2 + \sigma_2^2$	$V_1[w_{dam}\|z_1] = \sigma_2^2$	$V_2[w_{dam}\|z_1, z_2] = 0$

The expected value of post-climate change income given in period 0 is $E_0[w_{dam}] = \bar{w}_{dam}$, and climate uncertainty as represented by the variance in post-climate change income is $V_0[w_{dam}] = \sigma_1^2 + \sigma_2^2$. Once the climate signal z_1 is revealed in period 1, the nation updates the expected value of post-climate change income to be $E_1[w_{dam}] = \bar{w}_{dam} + z_1$; because only z_2 remains random, the variance becomes $V_1[w_{dam}] = \sigma_2^2$. How much of the initial climate uncertainty is resolved between periods 0 and 1 is defined as the uncertainty resolution speed S. The larger the S, the faster the resolution of uncertainty and the greater the benefits to delaying investment until period 1.

$$S = \frac{V_0[w_{dam}] - V_1[w_{dam}|z_1]}{V_0[w_{dam}]} = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} \tag{2}$$

Absent an incentive for investing in both periods, any positive uncertainty resolution speed will lead to no investment being made until period 1. Realistically, this incentive is provided by the practical preference for incremental investment to smooth consumption: governments would prefer to spread out spending for large projects over several years rather than have an outsized impact on a single year's budget. I incorporate this preference using CARA utility with coefficient of absolute risk aversion r, so that $U(c) = -e^{-rc}$. The payoff function then becomes

$$\pi = -e^{-r(w-a_0)} - e^{-r(w-a_1)} - e^{-r(w_{dam}+a_0+a_1)} \tag{3}$$

The optimal level of investment in each period can then be found through backward iteration. Optimal investment and expected payoffs can then be written in terms of the uncertainty resolution speed S and the initial level of climate uncertainty $V_0[w_{dam}] = \sigma_1^2 + \sigma_2^2$:

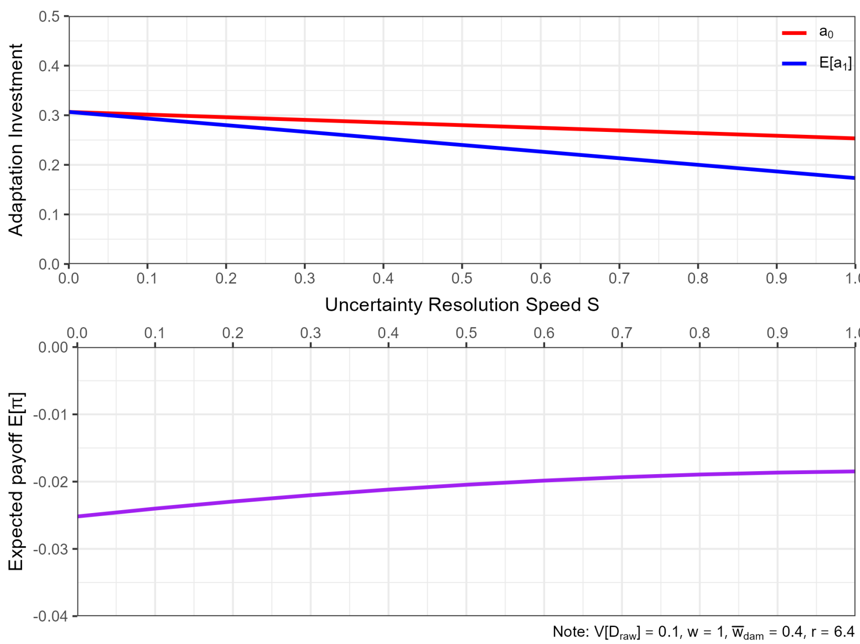
$$a_0 = \frac{1}{3}\left[w - \bar{w}_{dam} + \frac{r(\sigma_1^2+\sigma_2^2)}{2}\left[1 - \frac{S}{2}\right]\right] \tag{4}$$

$$a_1 = \frac{1}{3}\left[w - \bar{w}_{dam} + \frac{3z_1}{2} + \frac{r(\sigma_1^2+\sigma_2^2)}{2}\left[1 - \frac{5S}{4}\right]\right] \tag{5}$$

$$E[\pi] = -3e^{\frac{r}{3}\left[2w+\bar{w}_{dam}+\frac{r(\sigma_1^2+\sigma_2^2)}{2}\left[1-\frac{S}{2}\right]\right]} \tag{6}$$

The derivatives of a_1 and $E[a_2]$ with respect to S are both negative. This means that faster uncertainty resolution lowers the optimal level of investment in adaptation in both periods, holding the initial level of climate uncertainty constant. The increased benefits to delaying investment reduces the optimal level in the first period, while the lower variance reduces it in the second period. To illustrate, Figure 2 plots optimal expected investment and payoffs for increasing values of S. Expected payoffs increase with the uncertainty resolution speed; that is, faster uncertainty resolution improves the expected outcome.

Figure 2: Optimal Adaptation and Expected Payoff as S Increases



2.2 Generalized Framework

I generalize this toy model to a framework that better reflects the decision-making process around climate adaptation. In reality, policymakers receive updated information on climate change and make decisions for periods of a few years at a time over a longer timeline. I extend the number of periods available for investing in climate adaptation to T and allow income to vary over time. The effectiveness of each unit of investment in improving post-climate damage outcomes is represented by p.

The final period of the model, $T+1$, represents the consequences of climate change. Much of the synthesis aimed at policymakers highlights projections for the year 2100 as the benchmark value for climate damages. Though this benchmark value applies to 2100, it should be considered a lower bound for damages for each year that follows. I therefore separately weight the utility of the post-climate change period by β.

Figure 3: Generalized Framework Timeline

Period 0	Period $t \in [1, T]$	Period $T+1$
1. Learn $\bar{w}_{dam}, \sigma_1^2, ..., \sigma_{T+1}^2$	1. Learn z_t	1. Learn z_{T+1}
2. Receive income w_0	2. Receive income w_t	2. Realize $w_{dam} = \bar{w}_{dam} + \sum_{i=1}^{T+1} z_i$
3. Set investment a_0	3. Set investment a_t	3. Find $A = \sum_{i=0}^{T} a_i$
4. Gain $U(w_0 - a_0)$	4. Gain $U(w_t - a_t)$	4. Gain $\beta * U(w_{dam} - pA)$
$E_0[w_{dam}\|k_0] = \bar{w}_{dam}$	$E_t[w_{dam}\|k_t] = \bar{w}_{dam} + \sum_{i=1}^{t} z_i$	$E_{T+1}[w_{dam}\|k_{T+1}] = \bar{w}_{dam} + \sum_{i=1}^{T+1} z_i$
$V_0[w_{dam}\|k_0] = \sum_{i=0}^{T} \sigma_{i+1}^2$	$V_t[w_{dam}\|k_t] = \sum_{i=t}^{T} \sigma_{i+1}^2$	$V_{T+1}[w_{dam}\|k_{T+1}] = 0$

The timeline of the generalized framework follows a familiar cadence, depicted in Figure 3. In each period before the final period $T+1$, the nation learns information about the expected post-climate change income, receives income and decides the level of investment for the period, then gains utility from consuming the remainder. Income in each period is in terms of the counterfactual level of GDP in the absence of climate change.

The variance of climate damages in period 0 is $V[w_{dam}|k_0] = \sum_{i=1}^{T+1} \sigma_i^2$, which I label V. From the beginning, the nation is aware that the accumulation of realized signals will reduce the variance of the raw climate damages faced in future periods. In each period t, it updates the expected value and variance of w_{dam} given the set of information available in that period $k_t = \{a_i \,\forall\, i < t, z_j \,\forall\, j \leq t\}$:

$$E[w_{dam}|k_t] = \bar{w}_{dam} + \sum_{i=1}^{t} z_i \tag{7}$$

$$V[w_{dam}|k_t] = \sum_{i=t+1}^{T+1} \sigma_i^2 \tag{8}$$

Extending the model to $T+1$ periods implies a path of uncertainty resolution
.
speed $S = \{S_0, S_1, ..., S_T, S_{T+1}\}$ with S_t reflecting how much uncertainty is resolved in period t. This can be expressed as the magnitude of the decrease in climate damage variance given k_t as a proportion of the unconditional variance V.

$$S_t = \frac{V_t[w_{dam}|k_t] - V_{t-1}[w_{dam}|k_{t-1}]}{V_0[w_{dam}]} = \frac{\sigma_t^2}{V}, \tag{9}$$
$$\text{where } t \in [1, T+1],\ V = V_0[w_{dam}] = \sum_{i=0}^{T} \sigma_{i+1}^2$$

Assuming CARA utility, the expected payoff to be maximized by the policymaker is then

$$\pi = -\sum_{i=0}^{T} e^{-r(w_i - a_i)} - \beta e^{-r[\bar{w}_{dam} + \sum_{i=1}^{T+1} z_i + p \sum_{i=0}^{T} a_i]}$$

The path of optimal investment is the sequence $a = [a_1, a_2, ..., a_T]$, where investment for each period maximizes the expected payoff given k_t, the information set for that period. Solving for $a_t = \text{argmax } E[\pi|k_t]$ yields

$$a_t = w_t + \frac{\frac{ln(p\beta)}{r} - \bar{w} - p\sum_{i=t}^{T} w_i - \sum_{j=1}^{t}(z_j + pa_{j-1}) + \frac{r}{2}\sum_{k=t}^{T} \frac{\sigma_{k+1}^2}{1+(T-k)p}}{1 + (T - t + 1)p} \tag{10}$$

For every period $t > 1$, the analytic solution a_t can be written as a function of the previous period's investment a_{t-1} and speed of uncertainty resolution S_{t-1}. Optimal investment in the first period, which is deterministic, can be written as a function of the weighted sum of the uncertainty resolution speeds. That is,

$$a_0 = w_0 + \frac{\frac{ln(p\beta)}{r} - \bar{w} - p\sum_{i=0}^{T} w_i + \frac{Vr}{2}\left[1 - \sum_{k=1}^{T+1} \frac{(T-k+1)p}{1+(T-k+1)p} S_k\right]}{1 + (T+1)p} \tag{11}$$

$$a_t = a_{t-1} + [w_t - w_{t-1}] - \frac{z_t}{1 + (T-t+1)p} - \frac{Vr}{2}\frac{S_t}{[1 + (T-t+1)p]^2} \tag{12}$$

The optimal level of investment in adaptation technology increases with the variance of climate damages in period 0, V. However, the sequence of the uncertainty resolution speed S_t can vary even as V is held constant. Optimal adaptation investment will look different for a path in which the uncertainty resolution speed is initially high before slowing versus a path in which the speed is constant, even when the total amount of uncertainty resolved is the same. All else held equal, hastening the resolution of uncertainty leads to an alternate path of optimal adaptation with lower initial investments in adaptation.

3 Quantifying Climate Uncertainty

Three objects of interest affect the optimal path of adaptation in this framework: the current expected value of damages $\bar{w}_{dam}$, the magnitude of climate uncertainty associated with those damages V, and its uncertainty resolution speed S. To quantify these three objects, I construct a distribution of economic damage projections from predictions of how the climate will evolve. I source these predictions from outputs of Earth Systems Models (ESMs), which are the basis for most detailed projections of climate change. Each ESM run generates a gridded time series of climate realizations, such as temperature, given a greenhouse gas trajectory and initial conditions. Variation in the runs therefore can be attributed to three components: model uncertainty, scenario uncertainty, and internal variability.

These components evolve in different ways over time. The first component, model uncertainty, refers to variability in how well climate models represent true climatic processes, which decreases with improvements to climate science. The second, scenario uncertainty, reflects uncertainty around future trajectories (that is, scenarios) of climate change. This will resolve over time as mitigation efforts and past emissions accumulate. The final component of internal variability comes from the chaos inherent to climate, in which small differences in initial conditions can lead to significant differences in predicted climate trajectories. This is not expected to evolve in a directed way. All three influence the current climate uncertainty, but the speed of uncertainty resolution depends on only the paths of scenario and model uncertainty.

The expected value of damages can be estimated by taking the expected value across the ensemble of ESM runs after translating each into 2100 income after climate damages, normalized by the counterfactual 2100 income in the absence of climate change.[3] I quantify the climate uncertainty associated with those damages by accounting for the magnitude of its components. The uncertainty resolution speed of this climate uncertainty is not directly observable, but I explore its path through the two components expected to evolve over time.

3.1 Current Expected Damages and Climate Uncertainty

I begin by constructing the distribution of economic projections necessary to quantify the three components of climate uncertainty, which will also enable estimating the expected value of damages. The standard method from climate science exploits variation in model, scenario, and initial conditions, attributing the spread in scenario-

[3]Uncertainty around damage functions is considered economic rather than climate uncertainty. Here, I hold the damage function fixed to isolate climate uncertainty.

average damages to scenario uncertainty, the spread in climate model-average damages to model uncertainty, and the spread of damages within climate model given scenario to internal variability.[4] That is, for an ensemble of models m that each generate runs r for scenario s of realization x,

$$T = \underbrace{E[V_r(x|m,s)]}_{\text{Internal variability}} + \underbrace{E[V_m(E_r[x|m,s]|s)]}_{\text{Model uncertainty}} + \underbrace{E[V_s(E_r[x|m,s]|m)]}_{\text{Scenario uncertainty}} \tag{13}$$

Estimating this requires an ensemble of ESMs that each generate multiple runs over a shared suite of carbon trajectories. The computational costs of this were prohibitively high until recently, making it difficult to account for internal variability. However, advances in climate science have increased availability of such ensembles (See Lehner et al. (2020), among others). Multiple ESMs taking part in the sixth phase of the Climate Model Intercomparison Project (CMIP6) generate multiple runs for model-scenario dyads by perturbing the initial conditions. As members of CMIP, which provides the physical basis in each IPCC assessment, these ESMs produce comparable outputs using a standard set of greenhouse gas trajectories called Shared Socioeconomic Pathways (SSP) scenarios (O'Neill et al., 2016).

I collect every ESM run available for CMIP6 on the Pangeo Project, maintained by the Climate Data Science Lab at Columbia University.[5] Restricting my sample to ESMs that span at least two scenarios and have more than 5 runs per model-scenario dyad leaves 15 ESMs. I aggregate projections of yearly average temperatures between 2010 and 2100 from each run spatially to the country level and temporally to 30-year averages. This is translated into projections of 2100 country-level income

[4] This methodology is used to partition the three components of climate uncertainty in climate projections by Lehner and Deser (2023) and in U.S. economic projections by Schwarzwald and Lenssen (2022) among others. See Yip et al. (2011) for a fuller discussion of the methodology.

[5] This provides a convenient repository for official CMIP model outputs, which are published by various research groups.

after climate damages using the Burke et al. (2015b) damage function and normalized by the average 2100 income projection from RFFSP. The result is a distribution of economic damages that represents overall climate uncertainty.

Underlying this distribution are the 7 discrete SSP scenarios standard to CMIP6 models. SSP scenarios were established to provide illustrative trajectories of greenhouse gases and are not probabilistic; estimating Equation 13 without weighting the scenarios would be problematic. [6]. I therefore construct weights for each scenario to reflect their probability by drawing on the Resources for the Future Socioeconomic Projections (RFFSP) developed by Rennert et al. (2021).

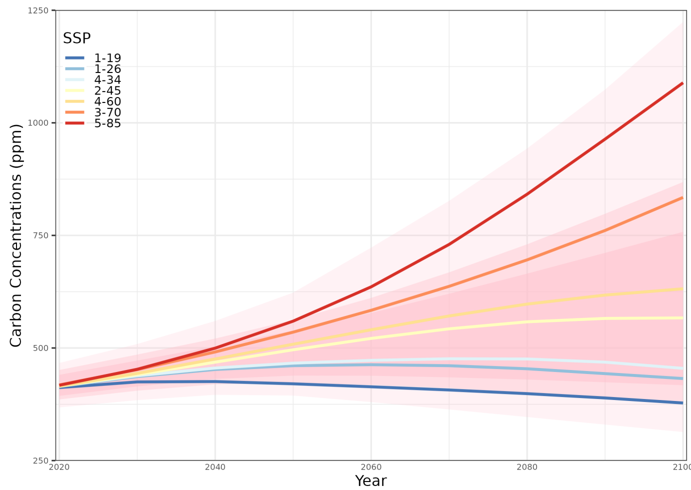
The RFFSPs provide probabilistic projections of carbon flow emissions translated into concentrations spanning 2020 to 2300.[7] I assign the SSP scenario closest to each RFF trajectory in 2100 concentrations as a first approximation, then use the frequencies to weight the SSPs in the decomposition.[8]

[6]Lehner et al. (2020) notes that averaging projections across all scenarios without assigning probabilities would not provide a "best-estimate" projection.

[7]While the original RFFSP comprises 10,000 equally likely trajectories, I grow the sample to 100,000 using generously provided replication files.

[8]The sample allows variants of the same model, following the IPCC methodology. I hope to incorporate Bayesian weights on models with relatively similar provenance as an extension.

Figure 4: Carbon Concentrations through 2100 in RFFSP



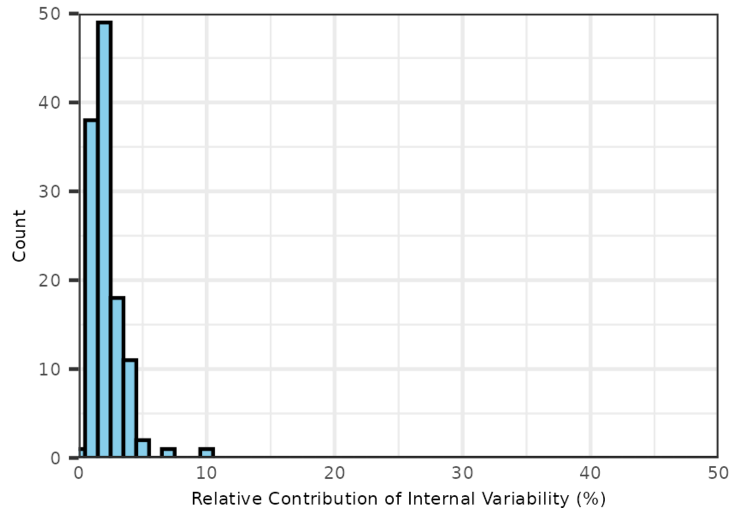
Shading represents minimum and maximum, 1st and 99th percentiles, and 5th and 95th percentiles of carbon concentration levels at each year. The lines denote standard greenhouse gas scenarios.

Using the ensemble of translated ESM projections and RFFSP scenario weights, I estimate the expected value of post-climate change income projections and its associated climate uncertainty. Some nations can expect benefits from climate change, but most impacts are severely negative; I restrict my sample to the 121 countries expecting damages. Taking Vietnam as my illustrative case, the expected income in 2100 as a share of the counterfactual income in the absence of climate change is 0.29, with climate uncertainty at 0.016.

These estimates used a limited sample of climate models in order to account for internal variability. However, I find that internal variability does not materially contribute to climate uncertainty around 2100 damages. Continuing with the example of Vietnam, internal variability comprises 3% of climate uncertainty in contrast to 55% from model uncertainty and 42% from scenario uncertainty. Figure 5 plots the histogram of the country-level contribution of internal variability. It demonstrates that internal variability is at most close to 10% and far smaller for most countries. [9]

[9] This is roughly in line with the finding by Schwarzwald and Lenssen (2022) that the contribution of internal variability to uncertainty in U.S. damage projections to be initially major but becomes

Figure 5: Internal Variability is Insignificant



Given its limited contribution to climate uncertainty, I move forward with a reduced decomposition that omits internal variability. This allows me to include all models in CMIP6 regardless of the number of runs available, increasing the number of models to 49. The reduced decomposition estimates climate uncertainty by partitioning the variance across ensemble means of every model-scenario dyad into model uncertainty and scenario uncertainty. For models that only have one run, the ensemble mean is that single run. I estimate Equation 14, weighting the scenarios using RFFSP as before.

$$T_{reduced} = \underbrace{E[V_m(E_r[x|m,s]|s)]}_{\text{Model uncertainty}} + \underbrace{E[V_s(E_r[x|m,s]|m)]}_{\text{Scenario uncertainty}} \tag{14}$$

I find that omitting internal variability does not significantly change estimates. The magnitudes are sufficiently similar that I proceed with the reduced decomposition results as the baseline for the rest of the paper, though estimates for expected post-climate income and climate uncertainty are both slightly higher for the restricted

less significant by 2100, though estimates are not entirely comparable due to differences in weighting.

decomposition.

Figure 6: Expected Damages and Climate Uncertainty

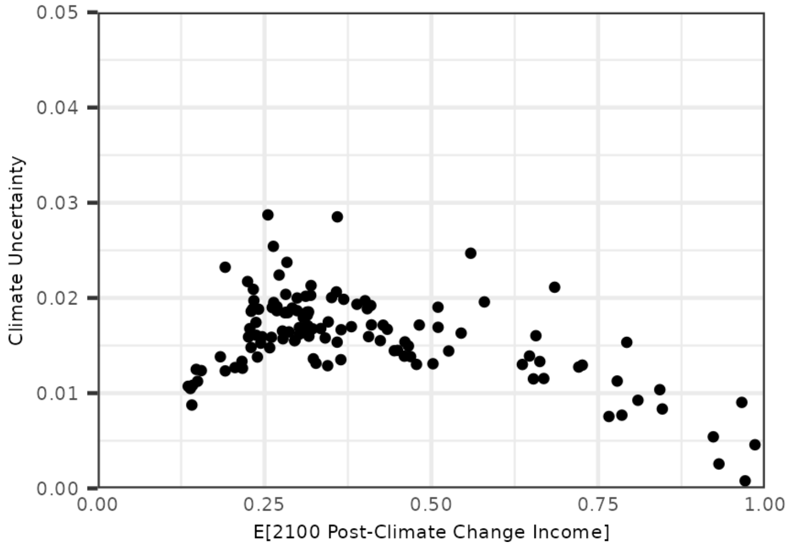
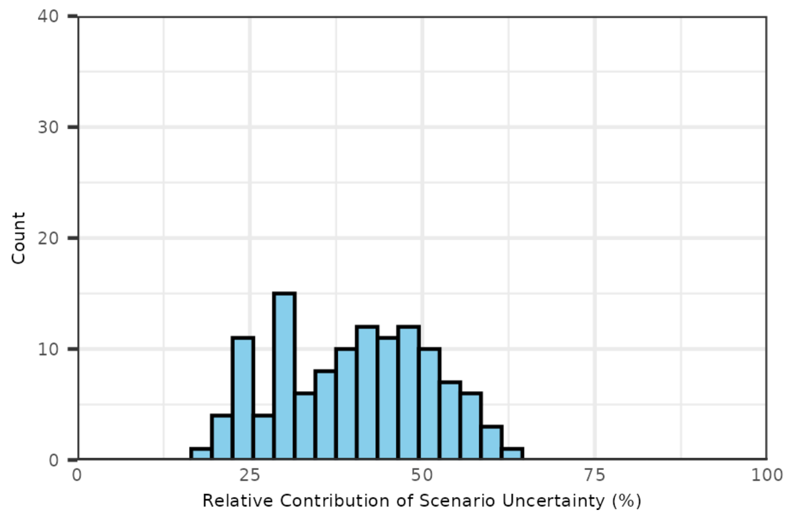


Figure 6 plots the resulting expected value of the post-climate change income against the estimated climate uncertainty for each country in the sample. For the example of Vietnam, including the full set of CMIP6 models and omitting internal variability shifts the expected 2100 post-climate damage income to 0.34 of the income in the absence of climate change. The climate uncertainty associated with this estimate is 0.025, roughly translating to a standard deviation of 0.16.

With the reduced decomposition, climate uncertainty can be partitioned into either model or scenario uncertainty. I calculate for each country the relative contributions of the two components.The histogram of the contribution of scenario uncertainty in Figure 7 suggests that model uncertainty comprises the greater part of climate uncertainty for most countries. Even so, scenario uncertainty is not trivial for any country.

Figure 7: Scenario Weights Significantly Reduce Scenario Uncertainty



3.2 Quantifying Uncertainty Resolution Speed

Having quantified the current magnitude of climate uncertainty and its components, I turn to examining how they evolve. Both scenario and model uncertainty change over time, but different factors are at play: Mitigation efforts and the accumulation of past emissions drive the path of scenario uncertainty, while the path of model uncertainty reflects improvements to climate science. Each will affect the evolution of climate uncertainty, which I represent through the sequence of its uncertainty resolution speed.

Though the path of climate uncertainty resolution speed cannot be directly projected, it can be constructed by compositing the paths of its components. For each period t, take V_t to be climate uncertainty with uncertainty resolution speed S_t, V_t^s to be scenario uncertainty with resolution speed V_t^s, and V_t^m to be model uncertainty with resolution speed S_t^m. Noting that $V = V_t^s + V_t^m$ and $S_t = \frac{V_{t-1} - V_t}{V_0}$,

$$S_t = S_t^s \frac{V_0^s}{V_0} + S_t^m \frac{V_0^m}{V_0} \tag{15}$$

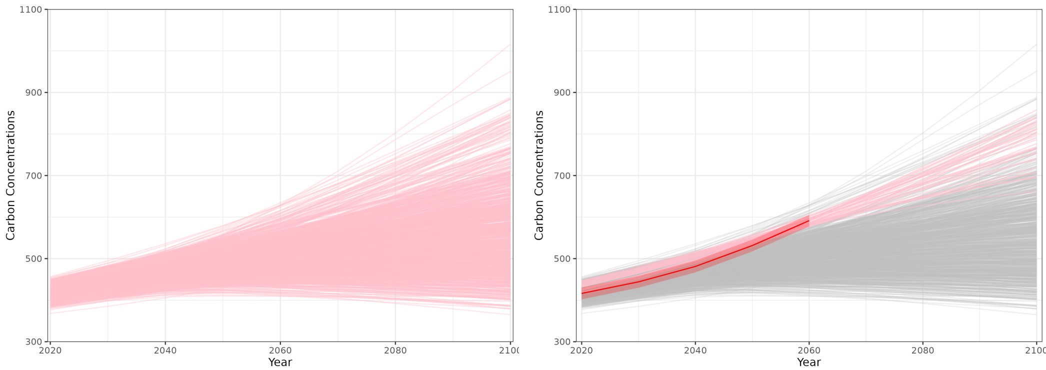
That is, climate uncertainty resolution speed for period t is the sum of the resolution speeds of model and scenario uncertainty, weighted by their relative contributions at time 0. As each component's relative contribution has been estimated in the previous section, I proceed to examine the path of uncertainty resolution for each component.

3.2.1 The Evolution of Scenario Uncertainty

A core assumption of this paper is that the unilateral actions of most individual countries cannot change the path of global carbon concentrations. Scenario uncertainty, though subject to large-scale mitigation, can be considered exogenous in the context of the country's adaptation decision problem. This allows me to estimate the evolution of scenario uncertainty with RFFSP trajectories of global carbon concentrations.

To begin, I define scenario to be the global carbon concentration at our anchor year of 2100, G_{2100}. Scenario uncertainty in the year 2020 is then represented by the variance of the full set of RFFSP trajectories $V_{2020}(G_{2100})$, as shown in Figure 8a. However, some of those trajectories will be rendered improbable once global carbon concentration is observed for 2030. Scenario uncertainty in 2030, represented by the expected value of the variance in feasible 2100 carbon concentrations given the 2030 value $E[V_{2030}(G_{2100}|G_{2030})]$, is necessarily lower than scenario uncertainty in the year 2020. This is the case for each subsequent decade, as represented in Figure 8b for 2060.

Figure 8: Decreasing Expected Variance in 2100 Carbon Concentrations



(a) Possible Paths in 2020

(b) Possible Paths in 2060

Note: Each line is a single trajectory of concentrations from RFFSP.

The path of scenario uncertainty in this context is represented by the expectation of the variance in G_{2100} across feasible trajectories for each decade.Trajectories are deemed feasible if they fall within a bandwidth of the observed value. [10] I calculate the variances of feasible G_{2100} taking each RFFSP trajectory as the observed path of carbon concentrations, then take the mean for each decade to calculate the expected variance. This yields scenario uncertainty at each decade from 2020 to 2090.[11] The scenario uncertainty resolution speed S_t^s for each decade t is then calculated as

$$S_t^s = \frac{E[V_t(G_{2100})] - E[V_{t-10}(G_{2100})]}{V_{2020}(G_{2100})}$$

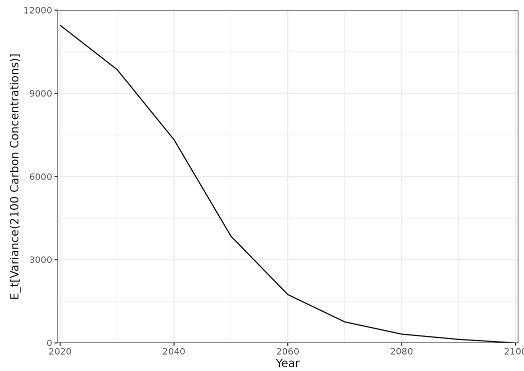
Figure 9 plots this path of scenario uncertainty and the corresponding path of uncertainty resolution speed. Scenario uncertainty in global carbon concentrations falls slowly for the first decades before declining rapidly by the mid-21st century. Since scenario uncertainty should not be affected by country-level policy actions, this path can be taken as given. I proceed to explore the resolution speed for the second

[10]The bandwidth is currently set to 1 standard deviation of carbon concentration draws at 2020, reflecting measurement error.

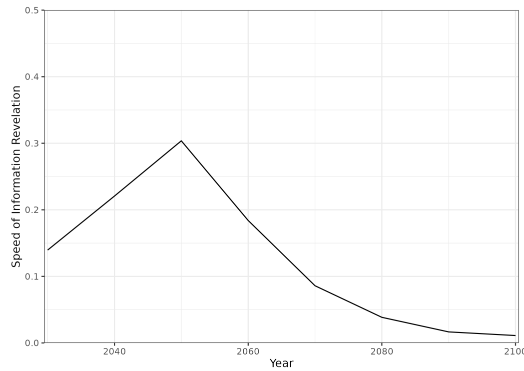
[11]For simplicity, I assume uncertainty is fully resolved in 2100.

component, model uncertainty.

Figure 9: Uncertainty & Resolution Speed in 2100 Carbon Concentrations



(a) Scenario Uncertainty



(b) Uncertainty Resolution Speed

3.2.2 The Evolution of Model Uncertainty

Unlike scenario uncertainty, the path of model uncertainty can be influenced by investing in climate research. Projections of climate change given a carbon scenario by different models are expected to increase in consensus as scientific advances improve our understanding of the climate system. It may however initially undergo a period of divergence with the diffusion of new findings. I examine the observed direction of model uncertainty spanning roughly 2008 to 2020 by approximating the trend of model uncertainty over two phases of the CMIP.

The earlier phase, CMIP5, began in 2008 to support the fifth IPCC Assessment Report (Chen et al., 2023).It established four standard greenhouse gas scenarios called representative concentration pathways (RCP 2.6, 4.5, 6.0, 8.5, with higher numbers indicating greater warming). Once CMIP6 was launched to provide model outputs for the sixth IPCC Assessment Report by 2020, it introduced SSP scenarios that incorporated socioeconomic narratives into the trajectories of greenhouse gases represented by RCP scenarios. Several SSPs are therefore analogous to RCP; SSP5-8.5

for example is the CMIP6 counterpart to RCP 8.5.[12] Many research institutes participated in both CMIP phases, often with updated versions of the same ESM. I therefore compare model uncertainty in each phase using a sample of scenarios and models from research institutes that appear in both phases. Table lists the scenarios and number of models included for each CMIP phase. This methodology is similar to that used by Jia et al. (2023) used to evaluate climate model performance across CMIP5 and 6 for China.

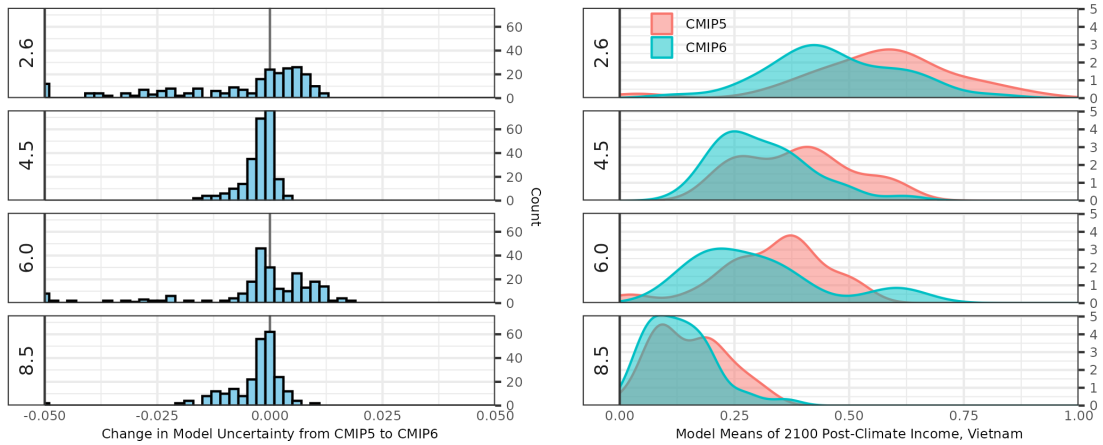
Table 1: Number of Models in CMIP5 and CMIP6

Phase	2.6	4.5	6.0	8.5	Models
CMIP6	34	34	7	35	36
CMIP5	25	33	18	35	35

Comparing model uncertainty by scenario across CMIP5 and CMIP6, I find that the direction of change varies by country. Figure 10a plots the histogram of country-level differences in model uncertainty from CMIP5 to CMIP6 by scenario. While many countries see decreases in model uncertainty, a fair number experience *increases* in model uncertainty, especially for Scenarios 2.6 and 6.0. Plotting the densities of estimates for the example of Vietnam in Figure 10b corroborates this pattern. While the distribution of estimates from CMIP6 all shift left from that of CMIP5, there is some divergence exhibited in Scenarios 2.6 and 6.0 shows some divergence.

[12] The greenhouse gas trajectories of both are not identical, but the two are considered comparable. See IPCC AR6 (Lee et al., 2021)

Figure 10: Model Uncertainty Change Between CMIP5 and CMIP6



Note: Censored at -0.05.

(a) Histogram of Change by Country (b) Distribution of Estimates, Vietnam

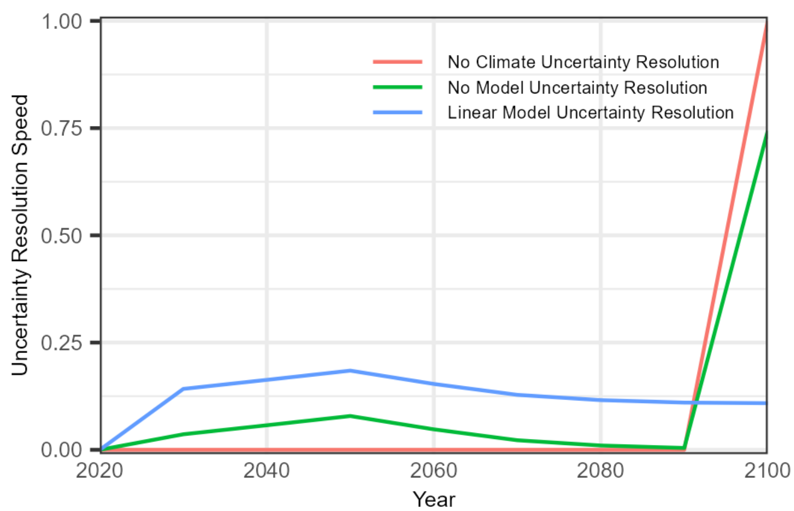
Given its limited data and time coverage, it is perhaps unsurprising that this exercise provides little information on the expected path of model uncertainty from present day to 2100. It may be that advances in science lead to initial disagreement that converges as ideas diffuse. Furthermore, realized model uncertainty may be larger even as the expectation of model uncertainty decreases. Whatever the cause, I am unable to estimate an expected path of model uncertainty resolution speed analogous to that of scenario uncertainty.

3.2.3 The Evolution of Climate Uncertainty

Though the previous exercise did not yield clear evidence of reductions in model uncertainty, it is probable that model uncertainty will still decrease with improvements in climate science over longer time spans. Climate research funding may then serve as a policy lever to affect the evolution of climate uncertainty through model uncertainty. I therefore construct sequences of climate uncertainty resolution speed for three possible paths of model uncertainty resolution.

The first path assumes no decrease in model uncertainty; that is, $S_t^m = 0$ and model uncertainty will remain constant at the current level present in CMIP6 until climate damages are realized. The second assumes a linear decrease in model uncertainty: $S_t^m = \frac{1}{T}$. I composite these two paths of model uncertainty resolution speed with the estimated path of scenario uncertainty resolution speed, weighting by the estimated relative contributions of each. To this, I add a sequence of zero *climate* uncertainty resolution speed for comparison. Figure 11 plots these sequences for Vietnam.

Figure 11: Paths of Uncertainty Resolution: Vietnam



The path of model uncertainty resolution speed shapes the overall path because it comprises a greater part of climate uncertainty. If there is no model uncertainty resolution over time, the amount of climate uncertainty resolved before 2100 is 25%. Assuming linear model uncertainty resolution, so that the resolution speed is constant, results in an intermediate path in which 90% of climate uncertainty is resolved by 2100. These three paths provide illustrative examples for exploring how climate uncertainty resolution affects optimal investment into climate adaptation.

4 Implications for Optimal Adaptation

To examine the policy implications of evolving climate uncertainty, I study the sequence of optimal adaptation investment for each constructed path of climate uncertainty resolution. The generalized framework in Section 2.2 yielded closed-form solutions of optimal adaptation investment over T periods. I set the period length to 10 years, rounding up from the seven or so years between releases of the IPCC assessment reports. As current estimates are dated to 2020 and the anchor year for damages is 2100, this results in $T = 7$ periods to make investments from 2020 to 2090 before damages are realized in period $T + 1 = 8$, represented by 2100.

Because the optimal levels for future periods depend on the information revealed, I calibrate the sequence of the expected optimal adaptation $E[a] = \{a_0, E[a_1], ..., E[a_T]\}$, in which

$$\begin{aligned} a_0 =& w_0 + \frac{\frac{ln(p\beta)}{r} - \bar{w} - p\sum_{i=0}^{7} w_i + \frac{Vr}{2}\left[1 - \sum_{k=1}^{8} \frac{(8-k)p}{1+(8-k)p} S_k\right]}{1+8p} \\ E[a_t] =& E[a_{t-1}] + w_t - w_{t-1} - \frac{Vr}{2}\frac{S_t}{[1+(8-t)p]^2} \ \forall \ t \in [1,7] \end{aligned}$$

according to Equations (11) and (12). Section 3 provides values for the expected post-climate damage income in 2100, $\bar{w}$; climate uncertainty, V; and the path of climate uncertainty resolution speed $S = \{S_1, S_2, ...S_8\}$ for each country facing climate damages in 2100. Investment, income, and post-climate damage income are all normalized as proportions of the counterfactual level of 2100 GDP per capita in the absence of climate change.[13] I weight the 2100 post-climate change outcome to persist for a century; that is, $\beta = 10$.[14] As climate change will continue to worsen

[13] This implicitly assumes zero population growth.
[14] This is in lieu of incorporating future discounting.

past 2100, this serves as an upper bound on utility over the 22nd century.

The coefficient of absolute risk aversion r for CARA utility can be expressed as

$$r = \frac{\text{Coefficient of Relative Risk Aversion}}{\bar{w}_{dam}} \tag{16}$$

I use a coefficient for relative risk aversion of 2 following the literature to calculate r.[15] This can be interpreted as the income the policymaker would be willing to give up to avoid climate uncertainty around damage, expressed as a proportion of the 2100 income in the absence of climate change.

Ideally, the path of income $w = \{w_0, w_1, ...w_T\}$ would follow an established projection. However, doing so exposes a limitation of the generalized framework. The fundamental tension between the benefits of waiting for uncertainty resolution and the desire to spread out investment over time is represented through consumption smoothing with CARA utility. As shown in Equation (12), this results in any increases in income from the previous period being put toward adaptation investment and income. Lacking alternatives for intertemporal transfers, an increasing path of income may lead to negative adaptation investment in the earlier periods.

The intuition is not altogether unrealistic. In the case of Vietnam, the average projected 2100 with climate damages using RFFSP is about two times that of 2020 income. If a nation is expected to be far richer in a few decades, delaying investment in climate adaptation in favor of other pressing priorities may indeed be optimal. My framework is however not equipped to evaluate this point, as it precludes the possibility of climate damages manifesting in earlier periods and abstracts away from other channels of investment and consumption smoothing. In order to isolate the effect of uncertainty resolution speed, I therefore proceed with a constant path of

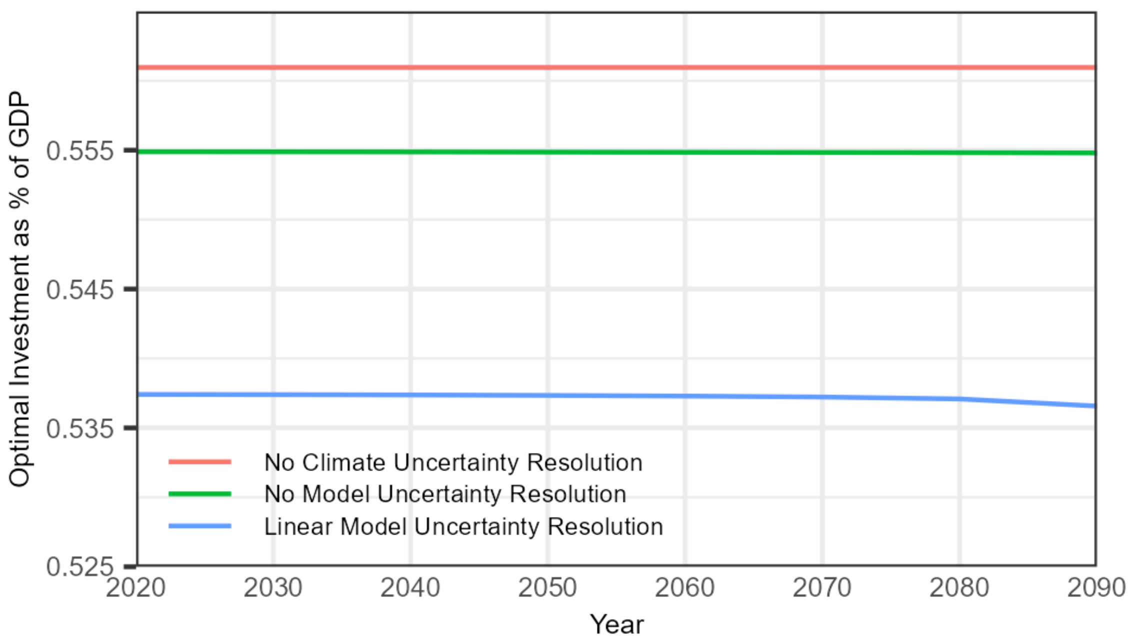
[15] For calibration, Elminejad et al. (2025) recommend using their corrected mean estimates of 1 for economics and 2–7 for finance.

income set at the 2100 counterfactual income in the absence of climate change for periods 0 to 7.

An estimate for the effectiveness of a unit of adaptation, p, is not easily available. However, the United Nations Environment Programme (2023) aggregates sectoral costs of climate adaptation to suggest a central estimate of 0.56% of GDP per year between 2020 and 2030 for developing countries. I therefore calibrate p for each country with this estimate as the target for the optimal investment in period 0 assuming no climate uncertainty.

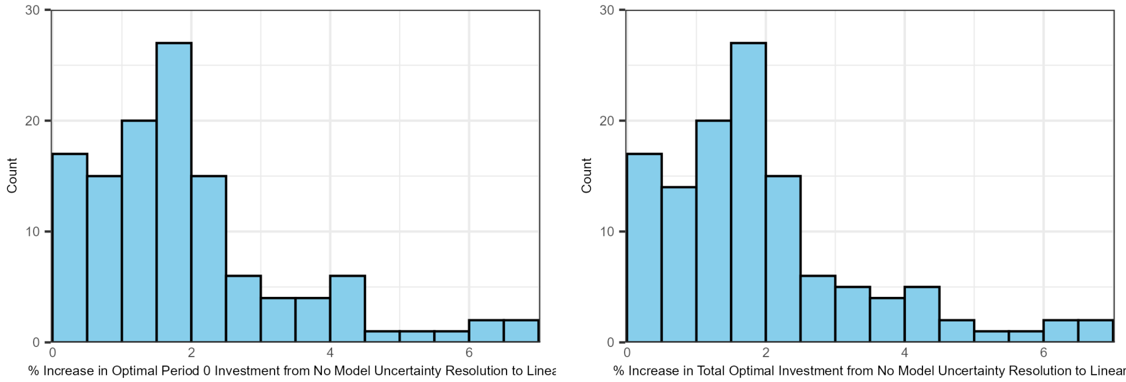
I then generate the sequence of optimal adaptation investment for each country given the three constructed paths of climate uncertainty resolution speed. The results indicate that faster uncertainty resolution meaningfully decreases the level of optimal investment across all periods. Considering first the example of Vietnam, Figure 12 plots the optimal level of investment in each period. The optimal level of initial investment is calibrated to be 0.56% of 2100 counterfactual income in the path without any resolution of overall climate uncertainty. The optimal initial investment is slightly lower given resolution of scenario uncertainty but not model uncertainty, at 0.554% of 2100 counterfactual income. Assuming steady resolution of model uncertainty leads to the lowest optimal initial investment at 0.537% of 2100 counterfactual income. The optimal level of investment for subsequent periods decreases more noticeably given linear model uncertainty resolution.

Figure 12: Paths of Optimal Adaptation Investment: Vietnam



I find evidence of similar savings across the full sample of countries expecting climate damages. Figure 13 compares optimal investment for the path of uncertainty resolution speed without model uncertainty resolution against that of linear model uncertainty resolution; Panel (a) plots the percentage increase in optimal initial investment from eliminating model uncertainty resolution, while Panel (b) plots the percentage increase in the total sum of expected investment. As expected, initial investment is higher when climate uncertainty resolution is slower. The increase in optimal level of initial investment without model uncertainty resolution can range from close to 0% to 7%, but hovers around 2% for the average country. The results are similar when comparing the expected total investment across the 80-year period. It must also be noted that the prescriptions of this model are most relevant for earlier periods before climate signals are accumulated. Overall, faster climate uncertainty resolution will decrease the optimal level of investment, benefiting nations seeking to engage in climate adaptation.

Figure 13: Optimal Investment for Zero vs. Linear Model Uncertainty Resolution



(a) Initial Investment a_0 (b) Total Expected Investment

5 Conclusion

Assuming it hastens the resolution of model uncertainty, climate science funding can reduce unnecessary investment and improve outcomes for nations vulnerable to climate change. The inverse also holds: Reducing support for research into the effects of climate change will decrease the benefits of delay, meaningfully increasing the level of investment optimal for managing climate risk. While we still have time, climate research itself is a cost-effective investment for the future.

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