# Mitigation + Adaptation

## What is the optimal climate change policy mix?

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**Abstract**

In dealing with climate change, how much should governments focus their effort on mitigation (emission reduction to prevent climate change) and on adaptation (coping with a changed climate)? Very little research has gone into pinning down which strategy is dynamically optimal under what kind of conditions. This paper contributes to this debate by developing a parsimonious optimal control model that identifies the steady state solution and its determinants, transition dynamics, the role of multiple countries, and the role of the non-linearity of climate change. Calibrated simulation results are provided to characterize the model. The results of this paper indicate that the adoption decision for mitigation and adaptation is determined by two key parameters: a climate change damage elasticity and an adjusted mitigation/adaptation cost ratio. Country heterogeneity in terms of emissions influences the policy choice strongly in favour of adaptation.

**Keywords**: climate change; mitigation; adaptation; optimal control theory.
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# 1 Introduction

In the debate about optimal responses to climate change, a central question concerns governments' choice of how much effort to expend on mitigation (emission reduction to prevent climate change) and how much effort to expend or adaptation (coping with a changed climate).[1] This paper contributes to this debate by developing a dynamic optimization (optimal control) problem that characterizes the optimal adoption of either or both of the two strategies. In terms of adopting any particular strategy, much depends on the underlying structural parameters, many of which remain marred by a large degree of uncertainty. Nevertheless, this paper furthers our understanding of the economic determinants that biases policy towards mitigation or adaptation.

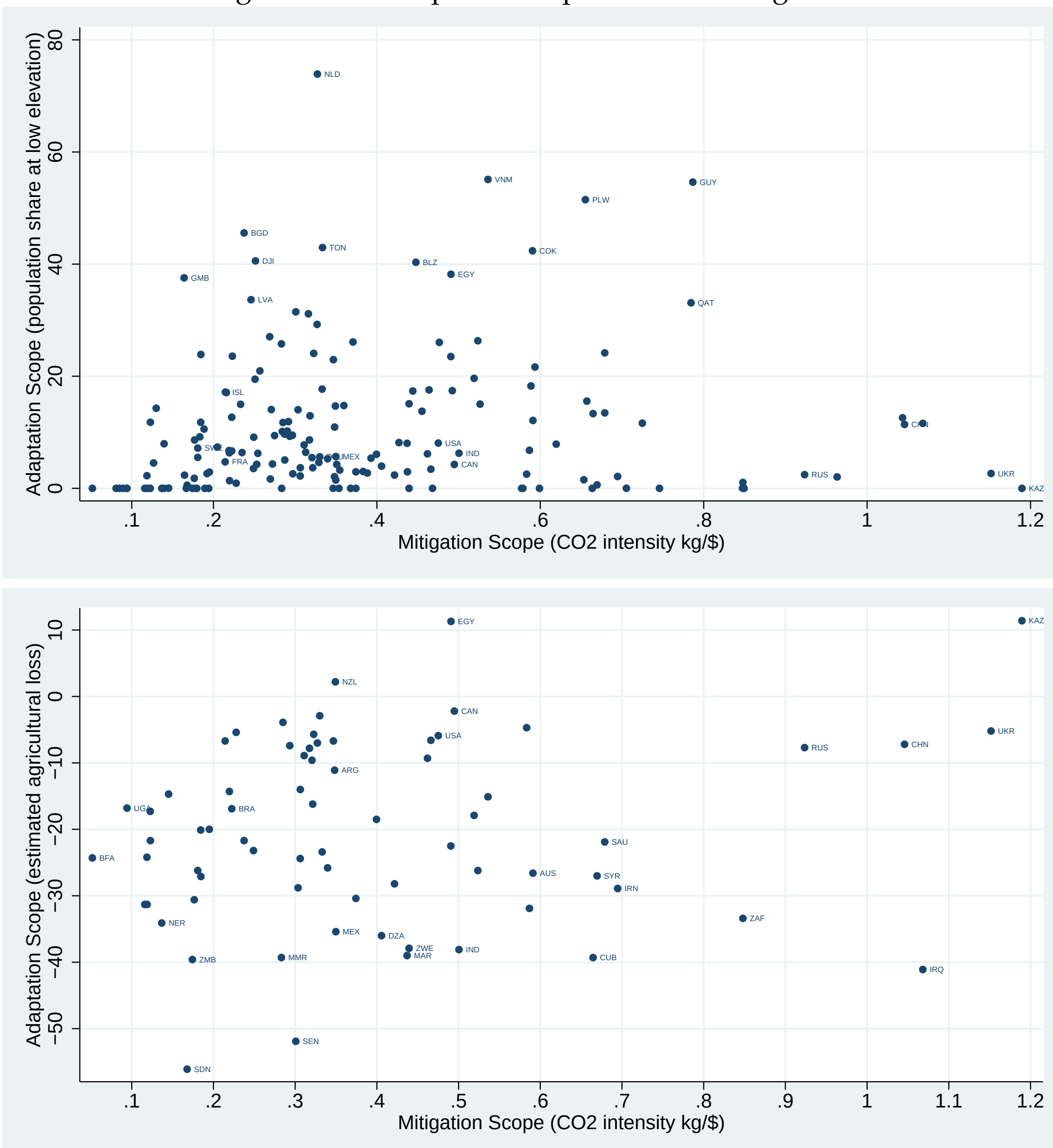
The key difference between mitigation and adaptation is the timing of the effort. Mitigation lowers the level of greenhouse gases, which slows down the build-up of the stock of greenhouse gases, which in turn lowers the potential for climate change consequences. On the other hand, adaptation does not reduce emissions, but instead manages the impact of climate change. Mitigation effort needs to commence early to have the desired effect, while adaptation effort can be postponed until actual climate change effects are noticeable. Naturally, society's time preference (inter-temporal discount rate) plays an important role in determining the optimal path. Unsurprisingly, societies that place a large weight on future utility (and thus have a low discount rate), will tend to put greater emphasis on mitigation than on adaptation. The purpose of this paper is to shed light on a variety of other factors that play a role in determining the optimal policy mix.

Another important difference between mitigation and adaptation is that the benefits from mitigation are shared globally, whereas the benefits from adaptation are mostly confined to countries that pursue adaptation policies. Put another way, mitigation is a global public good, while adaptation is a local public good. Consequently, while mitigation policies suffer from international coordination problems, adaptation policies remain national in scope. Countries may be more reluctant to create a global public good if they are unable to capture significant parts of the benefits. Adaptation therefore amounts to the default strategy if mitigation fails or is woefully insufficient. As Farnham and Kennedy (2010) point out, if come countries pursue adaptation, this makes it more difficult for the remaining countries to pursue mitigation. International cooperation is affected by individual country's choice to pursue on or the other strategy.

One salient feature of the choice problem relating to adaptation and mitigation is the cross-country heterogeneity both in potential for mitigation and adap-

[1] The Intergovernmental Panel on Climate Change (IPCC, 2007) defines mitigation as "technological change and substitution that reduce resource inputs and emissions per unit of output." Mitigation means implementing policies to reduce greenhouse gas emissions and enhance sinks. The IPCC defines adaptation as the "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." Examples include the raising river or coastal dikes or the substitution of more temperature-shock resistant plants for sensitive ones.

Figure 1: The scope for adaptation and mitigation




Notes: The scope for adaptation in the upper diagram is calculated as the percentage share of population living in a given country's low-elevation coastal zone (LECZ). Source: McGranahan et al. (2007). The scope for adaptation in the lower diagram is taken from table 5.8 column (H) in Cline (2007) that provides estimates of the expected percentage loss in agricultural output from climate change by 2080, without taking into account offsetting effects from carbon fertilization. The scope for mitigation is taken from the World Resources Institute *EarthTrends* database for year 2005, expressed in kg of carbon dioxide per dollar PPP (2005 basis).

tation as well as the (per-unit) cost of mitigation and adaptation. Countries exhibit hugely different mitigation potential as their economies are more or less carbon-intensive. Figure 1 illustrates this heterogeneity in carbon intensity for a large number of countries, and plots the carbon intensity against two measures of adaptation potential. The first such measure is the percentage share of a country's population living in its low-elevation coastal zone. The second measure is the percentage loss in agricultural output from climate change by 2080, as predicted by Cline (2007). Even if neither measure can capture the multi-dimensionality of climate change consequence and the need to adapt to them, the diagram nevertheless illustrates convincingly the scope of heterogeneity. This is an important starting point for the analysis in this paper.

Countries face different marginal mitigation costs depending on their existing emission intensity and industrial composition. The mix of energy sources probably plays a central role in determining these costs. For example, fuel switching (from coal to natural gas) is less costly than developing and deploying renewable energy sources. The cross-country dispersion in the cost of adaptation can be expected to be significantly larger if adaptation options are country-specific. Countries that face significant adaptation costs due to climate change are those that face (i) increasing desertification; (ii) flooding due to rising sea levels; (iii) increased probability of crop failure; or (iv) increasing intensity or frequency of extreme weather phenomena. For example, low-lying countries such as Bangladesh or the Netherlands tend to face very high adaptation costs compared to most other countries, as is illustrated in the top panel of figure 1.

There are many examples of dynamic models to analyze the economics of climate change; see for example Uzawa (2003). There has also been considerable practical discussions about the interactions between adaptation and mitigation; see for example Shalizi and Lecocq (2009). However, to date, there is very little work on the economics of choosing between adaptation and mitigation, with some notable exceptions. Kane and Shogren (2000) employ an endogenous risk framework at the national level to model the trade-off between mitigation and adaptation. Their model is comparative static in nature but allows for uncertainty in the distribution of the unknown state of the climate system. Ingham et al. (2005b,a); Tol (2005) find that an optimal response to climate change will contain a mix of both mitigation and adaptation. Some of these results will be challenged here: this mix will tend to occur more through policy heterogeneity across countries than through mixed policies at the level of individual countries. Felgenhauer and De Bruin (2009) provides an overview of many of the earlier results and introduces new results from incorporating adaptation into the standard *Dynamic Integrated Model of Climate and the Economy* (DICE) model (Nordhaus and Boyer, 2000). The paper closest in spirit to the work presented here is Settle et al. (2007). They also develop a dynamic model for the mitigation-adaptation trade-off, but focus on policy's effect to reduce the severity of catastrophic climate change. A particular useful feature of their approach is to incorporate learning behaviour. However, they share with earlier model that a mix of adaptation and mitigation is typically preferred.

Another recent theoretical paper on the mitigation-adaptation trade-off is Farnham and Kennedy (2010). Using a comparative static framework for their analysis, their focus is on how the introduction of adaptation changes the scope for international cooperation. A key result of their study is that country size dispersion matters: larger dispersion actually leads to lower global emissions, which in turn shifts countries away from adaptation and towards more mitigation.

In addition to studying the policy choice between adaptation and mitigation, this paper introduces three innovations. First, the damage from climate change is modeled explicitly as a non-linear function that is characterized by a critical threshold of climate change and the rapidity of climate change. Second, rather than introducing climate change into a conventional dynamic model of economic growth (including capital accumulation, population growth, and technological progress), the dynamics of the model in this paper are focused solely on the policy choice problem. Third, in order to study the non-linear dynamics of the model, a novel numerical simulation approach is introduced. This approach rigorously explores the relevant parameter domain through sampling, and characterizes the simulation results through regression analysis.

The remainder of this paper proceeds as follows. Section 3 introduces the basic dynamic optimization model with adaptation and mitigation, including its steady state solution, and section 4 discusses the emerging policy regimes. Section 5 introduces the empirical methodology and results. Section 6 discusses transition dynamics, and section 7 introduces uncertainty about climate change and analyzes how this affects the optimal policy mix. Section 8 turns to the (deterministic) case of two countries and analyzes how cross-country heterogeneity affects the optimal policy choice or policy mix. Section 9 summarizes the policy implications and concludes.

# 2 Context

While much of the public debate surrounding climate change has focused on mitigation strategies that were the objective of the Kyoto and Copenhagen rounds of negotiations, much less attention has been put on climate change adaptation. The Agrawala and Frankhauser (2008) and the World Bank have recently started to investigate the costs and benefits of adaptation policies more closely.

In 2008 the World Bank launched a study known as the "Economics of Adaptation to Climate Change" (EACC) with seven pilot countries—Bangladesh, Bolivia, Ethiopia, Ghana, Mozambique, Samoa and Vietnam—in order to help nations prioritize, sequence, and integrate robust adaptation policies into their development plans. The key problem is that the costs of adapting to climate change are not yet well known. In a recent report from the World Bank EACC Project Team (2009), early estimates from the EACC study put the costs of adaptation to climate change for developing countries in the range of US$75-100 billion a year globally for the period 2010 to 2050.[2] The report shows that the highest costs will be borne by East Asian and Pacific regions.

Even if greenhouse gas (GHG) concentrations in the atmosphere are stabilized at around 450ppm of $CO_2$(e), the estimated increase in temperatures at different locations around the earth is expected to lead to a higher incidence of adverse weather events, rising sea levels, and negative effects on agricultural production. Therefore, even if mitigation efforts are successful at reducing GHG emissions, there is dire need to plan for adaptation to climate change especially for those nations that will be most severely affected.

Climate change is expected to be non-linear rather than gradual. In particular, a sudden change in the Thermohaline Current (THC) in the Atlantic Ocean is considered a key example of such a non-linearity Schneider (2004). Another non-linearity may arrive from self-reinforcement of climate change. It has been argued that polar melting will reduce sunshine reflection and increase water temperatures, and thawing of permafrost tundra may release trapped methane, a more potent GHG than carbon dioxide. Weitzman (2009) has pondered the possibility of catastrophic climate change, the ultimate form of non-linearity.

While adaptation is a necessary part of the policy response to climate change, it is important to point out obvious limitations. Adaptation and mitigation are not perfect substitutes. During the fall of 2009, the Vancouver Aquarium ran a billboard advertisement campaign for its new Arctic wildlife exhibit with the slogan "adaptation is not an option," showing a clownfish-striped whale and a zebra-striped bear. The salient point is that some of the damage to the ecosystem may be irreversible, especially if the consequences of climate change are too rapid for ecosystems to adapt.

It should also be noted that adaptation strategies can be both private and public, and adaptive capacity is correlated strongly with the income level of countries. This poses a natural problem for an equitable distribution of the cost of climate change if it amounts to shifting the burden from rich polluters to poor non-polluters.

# 3 Model

The purpose of the model is to determine the optimal mitigation and adaptation policy mix, and thus it abstracts from a variety of conventional features found in economic optimal control models. In order to be parsimonious and concentrate on the key issues, the model contemplated here does not allow for (endogenous) economic growth, population growth, or technological progress. Introducing these features would lead to a more comprehensive set of analytic results, but they are not essential to characterize the driving factors of the policy mix.

Consider the dynamic control problem for a society that faces the consequences of a stock $z$ of greenhouses gases and has the option to either mitigate (abate)

[2] This amounts to just over 1% of world GDP, but is of course a much more significant share of GDP for developing countries.

emissions with effort $m \in [0, 1[$ or adapt to the consequences of $z$ with effort $a \in [0, 1[$. The society's utility in any given period is given by the constant relative risk aversion function

$$U(x) = \begin{cases} x^{1-\alpha}/(1-\alpha) & \text{for } \alpha > 0, \alpha \neq 1 \\ \ln(x) & \text{for } \alpha = 1 \end{cases} \tag{1}$$

where $\alpha$ is the coefficient of relative risk aversion, and $x$ is a measure of goods and services. Specifically, this measure $x$ is comprised of consumption $c$ and environmental damage $0 \leq d(z) < 1$. Consumption is impeded by the presence of environmental damage in a multiplicative way. Thus, $1-d(z)$ may be thought of as a quality measure of consumption. The present-value discounted welfare is then given by

$$W = \int_0^\infty U\left(c\left(1 - d(z)\right)\right) \exp(-\rho t) dt \tag{2}$$

where $\rho$ is the time preference (discount) rate as well as the inverse of the elasticity of inter-temporal substitution.

Changes in the emission stock of greenhouse gases $z$ are the difference between emissions $e = \kappa y(1-m)$ and natural decay $\delta z$. Emissions are proportional to production $y$, where $\kappa$ describes the unmitigated emissions intensity of production. Emissions are mitigated by the fraction $m$ at cost $M(m)$. Thus, the change in emissions is governed by

$$\dot{z} = \kappa y(1-m) - \delta z \tag{3}$$

The actual damage $d(z)$ depends on the potential damage $0 \leq Z(z) < 1$, but is reduced by the factor $(1-a)$ due to adaptation effort $a$ at cost $A(a)$:

$$d(z) = Z(z)(1-a) \tag{4}$$

The function $Z(z)$ can take on a variety of functional forms. Current research on climate change strongly suggests that this form is non-linear. The non-linearity of climate change can be considered to impose convexity on $Z(z)$ for small levels of GHGs and concavity for high levels of GHGs. Around a critical threshold $\hat{z}$, climate change will be most rapid.

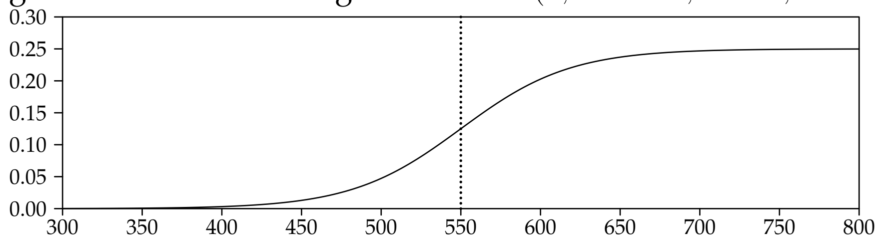
A particularly useful functional form to capture this is a variant of the logistic function:

$$Z(z) = \frac{\bar{Z}\exp(\omega(z-\hat{z})/\hat{z})}{1+\exp(\omega(z-\hat{z})/\hat{z})} \tag{5}$$

This function has the properties $Z(0) = \bar{Z}\exp(-\omega)/(1+\exp(-\omega))$,[3] $\lim_{z\to\infty} Z(z) = \bar{Z}$, $Z_z \equiv Z'(z) > 0$, as well as $Z''(z) > 0$ for $z < \hat{z}$ and $Z''(z) < 0$ for $z > \hat{z}$. The three parameters describe an upper damage level $0 < \bar{Z} < 1$ (the worst case scenario), a critical threshold $\hat{z}$, and a rapidity factor $\omega$ that characterizes the steepness of the change around the critical threshold $\hat{z}$. Figure 2 depicts the damage function with typical parameter values.

[3]This is a constant expression that is of little practical relevance as long as $Z(0) \ll \bar{Z}$.

Figure 2: Absolute Damage Function $Z(z; \bar{Z}=0.25, \omega=16, \hat{z}=550)$




The damage elasticity $\eta \equiv Z'(z)z/Z(z)$ is then given by

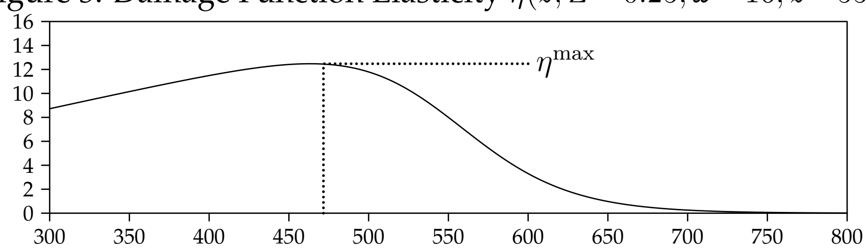
$$\eta(z) = \frac{\omega z/\hat{z}}{1 + \exp(\omega(z - \hat{z})/\hat{z})} \tag{6}$$

Note that $\eta(z)$ is bell-shaped and reaches a maximum at $[1 + \mathrm{W}(\exp(\omega - 1))]\hat{z}/\omega$, which implies that[4]

$$\eta \leq \eta^{\max} \equiv \mathrm{W}(\exp(\omega - 1)) \tag{7}$$

This function is upward sloping and nearly linear in $\omega$; specifically, $\eta^{\max} > 1$ when $\omega > 2$, and in general $\omega = 1 + \ln(\eta^{\max}) + \eta^{\max}$. Figure 3 depicts the elasticity function with typical parameter values, where the emission concentration at which $\eta^{\max}$ is reached lies below the threshold $\hat{z}$.

Figure 3: Damage Function Elasticity $\eta(z; \bar{Z}=0.25, \omega=16, \hat{z}=550)$




Consumption $c$ is equal to (constant) output $y$ without abatement or mitigation. In the presence of either, consumption is reduced by a fraction $0 \leq A(a) < 1$ and/or $0 \leq M(m) < 1$ that describe the cost of implementing adaptation or mitigation:

$$c = y[1 - A(a) - M(m)] \tag{8}$$

As $A(a)$ and $M(m)$ are cost functions, they must satisfy $A(0) = 0$, $A_a \equiv A'(a) > 0$, $A''(a) > 0$, $M(0) = 0$, $M_m \equiv M'(m) > 0$, $M''(m) > 0$. At later stages it will be expedient to assume particular functional forms in order to obtain closed-form solutions. While the quadratic cost function is a natural candidate, another functional form leads to algebraically more tractable results. These functions are

$$A(a) = -\gamma_a \ln(1 - a) \tag{9}$$
$$M(m) = -\gamma_m \ln(1 - m) \tag{10}$$

[4] $\mathrm{W}(\cdot)$ is the Lambert W function, the inverse function of $w \exp(w)$.

These cost functions have two advantages. First, marginal costs do not become zero as adaptation or mitigation effort approach zero; i.e., $A'(0) = \gamma_a > 0$ and $M'(0) = \gamma_m > 0$ are maintained. Second, these functions approach infinity as $a$ and $m$ approach one, thus indicating that full mitigation or full adaptation are unrealistically (i.e., infinitely) expensive. This rules out (implausible) full-adaptation or full-mitigation corner solutions. Marginal costs are $A'(a) = \gamma_a/(1-a)$ and $M'(m) = \gamma_m/(1-m)$, respectively. Therefore, these functions are nearly linear at low levels of effort and become increasingly convex as effort levels approach one.[5] It will also be useful to express the total climate change cost as a share of GDP:

$$\tau(a,m) \equiv A(a) + M(m) \tag{11}$$

The current-value Hamiltonian is

$$H = U\left(c(1-d(z))\right) + \lambda \dot{z} \tag{12}$$

See Chiang (1992) for methodological details. There are two first-order conditions that need to be satisfied for maximizing the Hamiltonian (12):

$$\frac{\partial H}{\partial m} = 0 \qquad \Leftrightarrow \qquad M_m = \frac{(-\lambda)\kappa[c(1-d(z))]^{\alpha}}{1-d(z)} \tag{13}$$

$$\frac{\partial H}{\partial a} = 0 \qquad \Leftrightarrow \qquad A_a = \frac{cd(z)}{y(1-a)(1-d(z))} \tag{14}$$

The costate variable $\lambda$ is negative because it represents a negative shadow price for the negative externality of GHGs. The motion equation for the state variable is given by (3), while the motion equation for the costate variable $\lambda$ is governed by

$$\dot{\lambda} = \rho\lambda - \frac{\partial H}{\partial z} = (\rho+\delta)\lambda + (1-a)Z_z c^{1-\alpha}(1-d)^{-\alpha} \tag{15}$$

In steady state, $\dot{\lambda} = 0$ and $\dot{z} = 0$. This implies:

$$z^* = (1-m^*)\kappa y/\delta \tag{16}$$

$$-\lambda^* = (1-a^*)Z_z(z^*)c^{1-\alpha}(1-d)^{-\alpha}/(\delta+\rho) \tag{17}$$

The two first-order conditions (13) and (14) can be used to simplify the two steady state equations (16) and (17).

$$1-\tau(m^*,a^*) = \gamma_m\left[1+\frac{\rho}{\delta}\right]\left[\frac{1-Z(z^*)(1-a^*)}{Z(z^*)(1-a^*)}\right]\frac{1}{\eta(z^*)} \tag{18}$$

$$1-\tau(m^*,a^*) = \gamma_a\left[\frac{1-Z(z^*)(1-a^*)}{Z(z^*)(1-a^*)}\right] \tag{19}$$

The two steady state equations (18) and (19) can be used in an elegant way to characterize the steady state. Noting that the left hand side of both equations are equal

[5] A cost function with similar behavior is $C(x) = \gamma x/(1-x)$, but leads to algebraic results that are slightly less tractable.

to $1-\tau$, the right hand sides of both equations must be equal as well. This implies that the damage elasticity $\eta$, which implicitly defines the optimal $m^*$ through $z^*$, is given by

$$\eta(z^*) = \left[1 + \frac{\rho}{\delta}\right] \frac{\gamma_m}{\gamma_a} \equiv \Gamma \tag{20}$$

The steady state requires that the damage elasticity equals the cost factor $\Gamma$, which will also play an important role below in determining under which conditions the mixed policy regime exists.

As $\eta(z^*)$ is bounded by $\eta^{\max}$, it is immediately clear that any policy involving mitigation (either pure mitigation or a mixed adaptation-mitigation approach) can only exist when $\eta(z^*)$ is sufficiently small.

**Proposition 1** *For a policy involving mitigation to exist, the cost ratio $\Gamma$ must be relatively small or the damage elasticity $\eta^{\max}$ must be relatively large. This requires that:*
*(i) the ratio of mitigation cost to adaptation cost ($\gamma_m/\gamma_a$) is small;*
*(ii) the ratio of time discount rate to emission decay rate ($\rho/\delta$) is small;*
*(iii) the rapidity of climate change ($\omega$) is large.*

When adaptation costs are very small or when a society has a high discount rate, an adaptation-only approach is significantly more desirable. A mixed adaptation-plus-mitigation approach also becomes less likely when climate change is very gradual. Only when climate change is sufficiently abrupt will a mixed approach be economically desirable.

# 4 Policy Regimes

The first-order conditions provide important insights into the existence of the mitigation-adaptation policy mix. In particular, condition (14) implies complementary slackness to ensure $a > 0$, and condition (13) implies complementary slackness to ensure $m > 0$.[6] Table 1 summarizes the conditions for the four possible policy regimes: no policy ($a = m = 0$), adaptation-only ($a > 0$, $m = 0$), mitigation-only ($a = 0$, $m > 0$), and mixed adaptation-mitigation ($a > 0$, $m > 0$).

Table 1: Policy Regimes

| | **No Mitigation** ($m = 0$) | **Mitigation** ($m > 0$) |
|---|---|---|
| **No Adaptation** ($a = 0$) | $\gamma_m$ and $\gamma_a$ "too high" | $\Gamma \leq \eta(z^*_{a=0})$ |
| **Adaptation** ($a > 0$) | $\Gamma \geq \eta(z^*_{m=0})$ and $\Gamma < \eta^{\max}$ | $\eta(z^*_{a=0}) < \Gamma < \eta(z^*_{m=0})$ |

[6] A Hamiltonian equation can be extended into a Lagrangian equation for inequality constraints. In the simple case where a control variable $u \geq 0$, this is equivalent to requiring the first-order condition to be $\partial H/\partial u = 0$ for $u > 0$ and $\partial H/\partial < 0$ for $u = 0$.

The extreme case is when no climate change policy is feasible ($a = m = 0$), and both policies are too expensive. In this case, the complementary slackness conditions that correspond to (14) and (13) require that

$$\gamma_m > \frac{\delta}{\delta+\rho}\eta(z_0^*)\frac{Z(z_0^*)}{1-Z(z_0^*)} \tag{21}$$

$$\gamma_a > \frac{Z(z_0^*)}{1-Z(z_0^*)} \tag{22}$$

where $z_0^* = \kappa y/\delta$ is the steady state without any policy. Further note that $d(z) = Z(z)$ when $a = 0$. The conditions imply that either climate change policy is too expensive

In the zero-adaptation mitigation-only case of $a = 0$, (14) holds as an inequality. Using the specific cost function (10) and making use of the steady-state solution for the zero-adaptation case (18) yields the condition $\Gamma < \eta(z_{a=0}^*)$, where $z_{a=0}^* = \kappa y(1-m_{a=0}^*)/\delta$. A further feasibility requirement is that $M(m^*) < 1$; climate policy cannot exceed the budget constraint. This implies that $m < 1-\exp(-1/\gamma_m)$; as the mitigation cost $\gamma_m$ increases, the feasible $m^*$ becomes ever smaller. The optimal $m^* > 0$ is given by:

$$1 - M(m_{a=0}^*) = \gamma_m\left[1+\frac{\rho}{\delta}\right]\left[\frac{1-Z(z^*)}{Z(z^*)}\right]\frac{1}{\eta(z^*)}; \quad z^* = \frac{\kappa y}{\delta}(1-m_{a=0}^*) \tag{23}$$

In the zero-mitigation adaptation-only case of $m = 0$, (13) holds as in inequality. Again using the specific cost function (10) and making use of (19) yields $\Gamma > \eta(z_{m=0}^*)$, where $z_{m=0}^* = \kappa y/\delta$. Compare the mitigation-only case with the previous zero-adaptation case: the steady-state damage elasticities will be different, and the direction of the inequality is reversed. Similar to the previous case, the budget constraint dictates that $a < 1-\exp(-1/\gamma_a)$. The optimal $a^* > 0$ is given by (19), where $\tau(m^*, a^*)$ simplifies to $A(a^*)$.

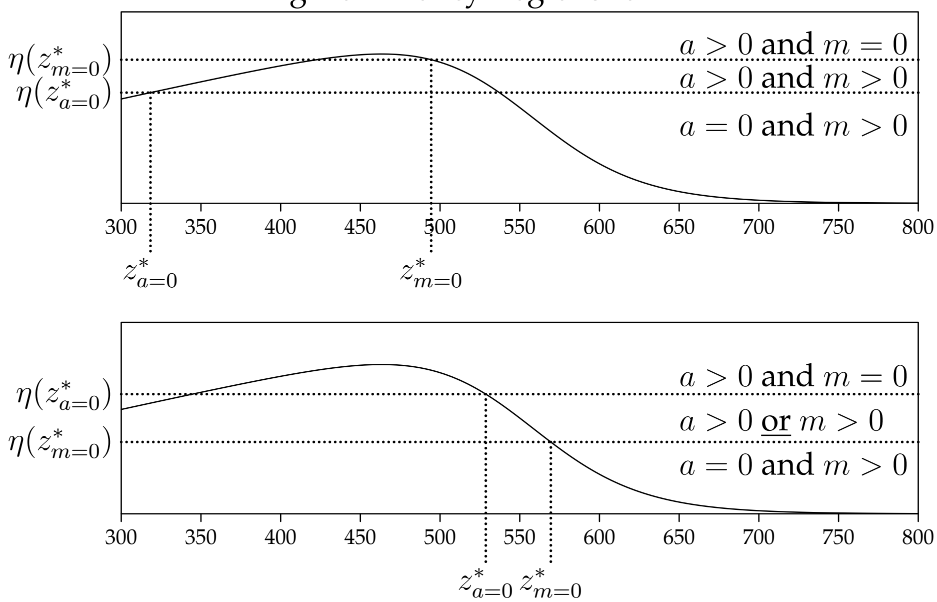
Combining the two special cases leads to the existence requirement for a mixed policy regime of $a > 0$ and $m > 0$:

$$\eta(z_{a=0}^*) < \Gamma < \eta(z_{m=0}^*) \tag{24}$$

Figure 4 illustrates two different configurations that can emerge. In the upper panel of the figure, the mixed policy exists if $\Gamma$ is bounded as defined in (24). In this configuration, when $\Gamma$ increases, the policy changes from mitigation-only to a mixed policy regime and then to an adaptation-only regime. This scenario is realized when $\eta(z_{a=0}^*) < \eta(z_{m=0}^*) < \eta^{\max}$, typically when $z_{a=0}^*$ lies to the left of $\tilde{z}$ where the damage elasticity reaches its maximum.

However, this is not the only feasible configuration. In the presence of mitigation, the corresponding steady state concentration level is lower than without mitigation, i.e., $z_{a=0}^* < z_{m=0}^*$. As was illustrated in figure 3, the damage elasticity function non-monotonous and therefore it is possible that $\eta(z_{m=0}^*) < \eta(z_{a=0}^*)$ when the steady state GHG level for the no-mitigation policy is far to the right of the

Figure 4: Policy Regions for $\Gamma$




damage elasticity maximum $\eta^{\max}$ at $\tilde{z}$. This configuration is illustrated in the lower panel of figure 4. Mathematically, the damage elasticity maximum $\tilde{z}$ tends to lie much before the climate change threshold $\hat{z}$, and empirical estimates suggest that $\hat{z}$ tends to be smaller than the no-mitigation steady state $z^*_{m=0}$. This means that the second scenario is empirically much more likely than the first scenario.

It is then possible that no mixed policy exists, as in the second scenario only a mitigation-only or an adaptation-only is optimal. Determining which of the two options is superior requires inspection of the total welfare, which can be ranked by

$$\Psi(a^*, m^*) \equiv [1 - \tau(a^*, m^*)]\, [1 - Z(z^*)(1 - a^*)] \tag{25}$$

If both adaptation-only and mitigation-only policies are feasible in the overlapping range (24), a comparison of $\Psi(a^*_{m=0}, 0)$ and $\Psi(0, m^*_{a=0})$ will determine which policy is superior.

The policy regime discussion identifies that a low $\Gamma$ increases the likelihood of mitigation policy, and a high $\Gamma$ increases the likelihood of adaptation policy.

**Proposition 2** *As $\Gamma$ increases, climate change policy shifts increasingly from mitigation to adaptation. This can be caused by an increase in the ratio of mitigation cost to adaptation cost ($\gamma_m/\gamma_a$)—mitigation becomes more costly relative to adaptation—or by an increase in the time discount rate rate ($\rho$). Societies with a high discount rate lean more towards adaptation than mitigation.*

The last part of the proposition needs emphasizing. The discount rate plays a central role in the discussions about climate change. In conventional models, a lower discount rate increases the urgency of adopting policy measures. Here, a lower discount rate shifts the balance between two competing policy measures.

# 5 Steady State Simulation

## 5.1 Methodology

Even with a relative simple structural model as the one outline above, the solutions for the steady state are non-linear and cannot be obtained as closed-form analytic expressions. It is therefore extremely difficult to explore the influence of individual parameters on the steady-state solution, or sign derivatives. Therefore, numerical methods need to be relied upon to determine the choice of climate change policy and the emerging policy variables. On a practical level, numerical simulation requires (i) calibration to plausible parameter values, and (ii) exploration of the relevant parameter domain in order to obtain a sense of the robustness of the results.

There are two problems with a numerical exploration of the relevant parameter domain. The first problem is that the relevant domain can become quite large. In the model above there are nine structural parameters ($\gamma_a$, $\gamma_m$, $\delta$, $\rho$, $\kappa$, $y$, $\omega$, $\hat{z}$, $\bar{Z}$). Suppose that there is plausible range for these parameters. Bracketing each parameter range into $m$ regions (or $(m+1)$ points), exploring the entire parameter domain for $n$ parameters requires $(m+1)^n$ simulations. With ten regions and nine parameters, this involves $11^9$ (2.36 billion) calculations of the steady state and any gradients. This may become computationally expensive or infeasible.

The second problem is that bracketing the relevant domain for each parameter equally is giving equal weight to less likely points (the fringes) and more likely points (the mid range). This equal weighting may give misleading results. It would be more sensible to weight the results from the mid range more heavily than the results from the fringes.

Sampling provides a practical alternative to brute force domain exploration. Sampling parameters from a particular statistical distribution and then running a large but manageable number of calculations—thousands rather than billions—provides a suitable exploration of the parameter domain. The first practical questions is the choice of statistical distribution. Infinite-tailed distributions such as the normal distribution are not useful because drawing parameters from outside the valid range could violate parameter constraints or imply implausible alternatives. Otherwise there is no theoretical imperative that guides the choice of statistical distribution. The simplest distribution that assumes a fixed range and provides greater weighting to the mid range than the fringes is the triangular distribution. Let $L$, $M$, and $H$ denote the low (minimum), mid (mode) and high (maximum) of this distribution. This is particularly useful distribution because a researcher is typically able to identify a valid range ($L$ and $H$) and a "preferred" or "high-likelihood" midpoint ($M$). Detailed information about the triangular distribution (probability density function, etc.) is contained in the Appendix. With this tool at hand, it is now possible to explore the parameter domain stochastically in a manner that is computationally feasible and weighted more heavily towards the more likely parameters. Parameter domain exploration thus involves the following four steps:

1. Draw a sequence of $N \geq 5,000$ random parameter sets, where each of the

$K$ parameters $p_k$ is drawn independently from a triangular distribution with low point $p_k^L$, high point $p_k^H$, and mode point $p_k^M$.

2. Calculate $N$ solutions of the steady state (and corresponding gradients) of the $p$ parameters in the steady state.
3. Summarize the frequency of different policies and analyze them through a (multinomial) discrete choice regressions. Also summarize the steady state solutions by computing means and standard deviations, and analyze them by regressing the outcomes on a simple linear model with the model parameters as regressors. a positive sign.

The last step involves linearizing the model and using a logit or probit model to explore the choice of policy (none, adaptation-only, mitigation-only, or mixed), and using ordinary least squares to explore the relative influence of different parameters on the steady-state solution. For the latter, it is often useful to consider linearization as a first-order Taylor series approximation around the mean (or mode) of the parameter. Using log-demeaning, i.e., transforming a variable by $\ln(x_k/x_k^{\text{mean}})$, captures the variation around the parameter mean symmetrically and is particularly easy to interpret either as an elasticity in the case of an OLS regressions, or as a marginal effect in a logit regression.

## 5.2 Calibration

Table 2 introduces parameter ranges for the key variables in the model. The lower and upper bounds for the assumed triangular distribution are indicated in columns L (low) and H (high), and the preferred values is indicated in column M (middle). There are nine parameters in the model, three environmental parameters and six economic parameters.

Table 2: Parameter Ranges

| Parameter | Symbol | L | M | H | Mean | S.D. |
|---|---|---|---|---|---|---|
| climate change rapidity | $\omega$ | 3.00 | 12.0 | 24.0 | 13.1 | 4.30 |
| criticality threshold | $\hat{z}$ | 480 | 600 | 720 | 598 | 49.0 |
| damage ceiling | $\bar{Z}$ | .050 | .200 | .350 | .202 | .061 |
| regeneration speed | $\delta$ | .015 | .018 | .021 | .018 | .001 |
| time discount rate | $\rho$ | .010 | .050 | .080 | .047 | .014 |
| mitigation cost | $\gamma_m$ | .050 | .100 | .150 | .100 | .020 |
| adaptation cost | $\gamma_a$ | .010 | .100 | .300 | .136 | .059 |
| scale of economy | $y$ | 55.0 | 65.0 | 75.0 | 65.0 | 4.13 |
| emission intensity | $\kappa$ | .080 | .160 | .320 | .188 | .051 |
| Policy Factor | $\Gamma$ | | | | 3.41 | 2.72 |
| Maximum damage elasticity | $\eta^{\max}$ | | | | 9.86 | 3.87 |
| No-policy steady state | $z^0$ | | | | 682 | 194 |

Notes: L=lower bound; M=mode; H=upper bound; S.D.=standard deviation

The regeneration speed $\delta$ is based on atmospheric modeling that suggests that it takes about 40-50 years to reduce 50% of $CO_2$ concentrations. Thus the preferred parameter for $\delta$ is about 1.8%. Some economists have assumed values as high as 4% (Uzawa, 2003, p. 246). This appears to be implausible large as it suggests a half-life of $CO_2$ concentrations of only 18 years and there seems to be little basis for assuming relatively high values of $\delta$.

The scale of the world economy is expressed in trillion PPP-$ as reported by the World Bank Development Indicators for 2008. This parameter is by far the easiest to pin down, and the variation around this parameter is allowing for considerable mismeasurement.

The emission intensity parameter is based on a regression of atmospheric $CO_2$(e) concentrations (in ppmv) at the Mauna Loa measurement station on World GDP, the slope from a linear regression for the upper bound, the slope from a time-differenced regression for the mode, and the slope minus one standard deviation from a time-differenced regression for lower bound. This is obviously a rather ad-hoc shortcut to capture the effect of economic activity on $CO_2$(e) concentrations. The difficulty of capturing this parameter accurately arises from the problem of translating emissions into emission concentration contributions.

The time discount rate ranges between 1% and 8%, with a typical value of 4%. This range reflects the Stern/Nordhaus discussion about what amounts to an appropriate time preference rate. The *Stern Report* had argued that a very small discount rate is appropriate, whereas Nordhaus (2007) had argued that real pretax returns on U.S. corporate capital over the last four decades had averaged about 7%.

To calibrate the criticality threshold, recall that the unmitigated steady state emission concentration is $z^0 = \kappa y/\delta$. With the mode values for these parameters, $z^0$ is about 680 ppmv. The most difficult parameter to pinpoint is the rapidity factor $\omega$. The non-linearity of climate change is still subject to much research and much uncertainty. A relatively wide range (3–24) covers a range that provides a nearly linear behavior at the low end and a very rapid transition at the high end.

Calibrations always remain subject to criticism. Many of the choices are imprecise at best and speculative at worst. Relying on parameter ranges instead of a single set of calibrated parameters provides some needed reassurance that qualitative results are sufficiently robust.

## 5.3 Results

Table 3 provides summary statistics for the simulation results based on 5,000 random draws of parameter sets. The particular set of parameter ranges led to about half the cases with a mitigation policy, just over 10% of the cases with adaptation, and the remainder without policy. Quite revealingly, a mixed regime of adaptation and mitigation did not emerge at all. When mitigation was chosen, about 26% of emissions tended to be reduced at a cost of 3.2% of world output, whereas when adaptation was chosen, 47% of the deleterious consequences of climate change were compensated at a cost of 5.1% of world output. When an adaptation policy was chosen, the steady-state emission concentration tends to be much higher than with mitigation or no policy at all, and consequently the (unadapted) climate change damage also tends to be the highest—about twice as large as with mitigation. The 'no policy' regime can be the result of two circumstances: adopting policies is too expensive, or adopting policies is unnecessary because the steady-state equilibrium is on the benign side of the damage curve.

How do particular parameter choices influence the adoption of the three regimes—mitigation, adaptation, or neither? Table 4 shows the results from a simple logit regression on the nine model parameters. The dependent variable in column (1) is an indicator for the adoption of 'no policy' with respect to the baseline of 'any policy', and the dependent variable in column (2) is an indicator for adopting an adaptation policy with respect to the baseline of adopting a mitigation policy (thus excluding the 'no policy' cases). The regressors are log-demeaned so that for any regressor $x_k$ with mean $x_k^{\text{mean}}$, the transformed regressor is $x_k^\circ \equiv \ln(x_k/x_k^M)$. This transformation provides for an easier interpretation of the estimated coefficients, as evaluating the regression at the mean means evaluating them at zero.[7] This means that the magnitude of the estimated coefficients are directly comparable.

With respect to the 'no policy' regime, five parameters play a crucial role (magnitude above 5) while four others have a more diminished role (magnitude below 2). As the scale of the the economy or the emission intensity rises, avoiding any climate change policy becomes less likely. In other words, small countries are much more likely to opt out of climate policies than large countries. Similarly, as the damage ceiling rises, it becomes more and more likely that a country will adopt a climate change policy. Unsurprisingly, if the natural regeneration rate increases, avoiding climate change policy altogether becomes a much more likely outcome as well. The effect of changes in mitigation and adaptation cost have the expected, but relatively small, effect: they reduce the probability of adopting a climate change policy. The most interesting results concern the parameters that describe the non-linearity of climate change. A rise in the criticality threshold makes it much less likely that a policy is adopted because climate change becomes less likely. An increase in climate change rapidity has a relative small effect. As climate change becomes more non-linear, adopting a climate change policy becomes more likely.

Column (2) in table 4 provides results for the choice between mitigation and adaptation. The numerical results confirm immediately the theoretical prediction 2. Increases in mitigation cost or time discount rate, or decreases in adaptation cost or regeneration speed, will unambiguously bias the policy choice from mitigation towards adaptation. Any of the described parameter changes will increase $\Gamma$. Also unsurprising is the effect of an increase in the world economy or an increase in the world's average emission intensity. Both will shift up the steady state GHG concentration $z^*$, which will make it less likely that mitigation policy will be effective, and will make it more likely that adaptation policy will be necessary. As

[7] In the logit model, $\Lambda(\mathbf{x}'\boldsymbol{\beta}) \equiv \exp(\mathbf{x}'\boldsymbol{\beta})/(1+\exp(\mathbf{x}'\boldsymbol{\beta}))$, and thus $\partial \mathrm{E}[y|\mathbf{x}]/\partial \mathbf{x} = \Lambda(\mathbf{x}'\boldsymbol{\beta})[1-\Lambda(\mathbf{x}'\boldsymbol{\beta})]\boldsymbol{\beta}$. Evaluated at the sample means for $x_i$ reduces $(\mathbf{x}'\boldsymbol{\beta})$ to the intercept $\beta_0$. Let $B \equiv \Lambda(\beta_0)[1-\Lambda(\beta_0)]$. Then $\partial \mathrm{E}[y|\mathbf{x}]/\partial x_i = B\beta_i$.

Table 3: Simulation Results: Policy Choice Summary Statistics

| Parameter | Symbol | No Policy | Adaptation | Mitigation |
|---|---|---|---|---|
| policy frequency | | 38.0% | 11.0% | 51.0% |
| adaptation effort | $a$ | | $.469\ (.248)$ | |
| mitigation effort | $m$ | | | $.264\ (.145)$ |
| total cost | $\tau$ | | $.051\ (.029)$ | $.032\ (.022)$ |
| welfare measure | $\Psi$ | $.957\ (.050)$ | $.870\ (.054)$ | $.930\ (.029)$ |
| emission concentration | $z^*$ | $555\ (177)$ | $822\ (172)$ | $527\ (48.1)$ |
| climate change damage | $Z(z^*)$ | $.043\ (.050)$ | $.084\ (.044)$ | $.039\ (.018)$ |

Note: standard errors are shown in parentheses.

Table 4: Simulation Results: Policy Choice (Logit Regressions)

| | Outcome<br>Baseline | No Policy<br>All other | Adaptation<br>Mitigation |
|---|---|---|---|
| Parameter | Symbol | (1) | (2) |
| intercept | | $-1.47^c$ (0.085) | $-2.94^c$ (0.145) |
| climate change rapidity | $\omega$ | $-0.71^c$ (0.180) | $-3.77^c$ (0.280) |
| criticality threshold | $\hat{z}$ | $8.37^c$ (0.824) | $-3.09^b$ (1.096) |
| damage ceiling | $\bar{Z}$ | $-5.16^c$ (0.263) | $-1.32^c$ (0.314) |
| regeneration speed | $\delta$ | $8.10^c$ (0.984) | $-5.57^c$ (1.338) |
| time discount rate | $\rho$ | $0.67^c$ (0.186) | $1.07^c$ (0.275) |
| mitigation cost | $\gamma_m$ | $1.25^c$ (0.315) | $1.51^c$ (0.424) |
| adaptation cost | $\gamma_a$ | $1.79^c$ (0.149) | $-2.43^c$ (0.197) |
| scale of economy | $y$ | $-7.72^c$ (1.060) | $5.74^c$ (1.515) |
| emission intensity | $\kappa$ | $-8.64^c$ (0.381) | $2.93^c$ (0.453) |

Note: Standard errors in parentheses. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts $^a$, $^b$, and $^c$, respectively. All regressors are normalized through a $\ln(x_{ik}/x_k^{\text{mean}})$ transformation.

Table 5: Simulation Results: Policy Intensity (OLS Regressions)

| | | Adaptation | | Mitigation | |
|---|---|---|---|---|---|
| Parameter | Symbol | Linear | Log-Lin | Linear | Log-Lin |
| intercept | | $0.240$ | $-5.697$ | $0.219^c$ | $-6.115^c$ |
| | | $(0.204)$ | $(4.346)$ | $(0.023)$ | $(1.746)$ |
| climate change rapidity | $\omega$ | $0.007^c$ | $0.137$ | $-0.000$ | $0.042$ |
| | | $(0.002)$ | $(0.098)$ | $(0.000)$ | $(0.050)$ |
| criticality threshold | $\hat{z}$ | $-0.000^b$ | $-0.220$ | $-0.001^c$ | $-2.953^c$ |
| | | $(0.000)$ | $(0.472)$ | $(0.000)$ | $(0.185)$ |
| damage ceiling | $\bar{Z}$ | $2.210^c$ | $1.322^c$ | $0.355^c$ | $0.399^c$ |
| | | $(0.127)$ | $(0.124)$ | $(0.017)$ | $(0.059)$ |
| regeneration speed | $\delta$ | $-22.55^c$ | $-1.550^a$ | $-32.86^c$ | $-3.243^c$ |
| | | $(6.680)$ | $(0.623)$ | $(0.727)$ | $(0.221)$ |
| time discount rate | $\rho$ | $-0.860$ | $0.041$ | $-1.268^c$ | $-0.338^c$ |
| | | $(0.563)$ | $(0.128)$ | $(0.062)$ | $(0.043)$ |
| mitigation cost | $\gamma_m$ | $-0.206$ | $-0.089$ | $-0.746^c$ | $-0.307^c$ |
| | | $(0.346)$ | $(0.176)$ | $(0.044)$ | $(0.072)$ |
| adaptation cost | $\gamma_a$ | $-4.017^c$ | $-0.915^c$ | $-0.040^a$ | $-0.054$ |
| | | $(0.153)$ | $(0.066)$ | $(0.016)$ | $(0.034)$ |
| scale of economy | $y$ | $0.006^b$ | $0.382$ | $0.010^c$ | $3.539^c$ |
| | | $(0.002)$ | $(0.649)$ | $(0.000)$ | $(0.239)$ |
| emission intensity | $\kappa$ | $1.937^c$ | $1.512^c$ | $3.313^c$ | $3.616^c$ |
| | | $(0.178)$ | $(0.201)$ | $(0.021)$ | $(0.075)$ |
| number of observations | | 275 | 275 | 1,274 | 1,274 |
| regression $R^2$ | | 0.775 | 0.529 | 0.955 | 0.671 |

Note: Standard errors in parentheses. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts $^a$, $^b$, and $^c$, respectively.

with the results from column (1), the interesting results concern the climate change parameters. As the damage ceiling $\bar{Z}$ goes up, so does the probability of adopting mitigation. A stronger effect towards mitigation is exerted by increases of the criticality threshold or climate change rapidity. Intuitively, as the criticality threshold recedes, there is more scope for mitigation effort to prevent crossing of the threshold. The intuition for climate change rapidity is similar but depends crucially on where the typical steady state concentration lies relative to the critical threshold. If the no-policy steady-state level is typically larger than the criticality threshold, more rapid climate change will extend the region where mitigation policy can prevent most of the adverse effects of climate change.

With respect to the key climate change parameters, the numerical results suggest the following

**Proposition 3** *As either the climate change criticality threshold or the climate change rapidity (non-linearity) increase, mitigation policy becomes more likely than adaptation policy. However, an increase in the criticality threshold will also raise the probability of adopting no policy at all, while more rapid climate change slightly increases the probability of adopting some climate change policy.*

The last set of questions concerns the effort level for adaptation and mitigation conditional on either policy being adopted. Table 5 provides numerical results based on linear and log-linear OLS regressions. In the linear case, parameters are untransformed, and in the log-linear case, parameters are de-meaned and expressed in logarithms. The obvious results concern the cost parameters. Increases in mitigation cost decrease mitigation effort, while increases in adaptation cost decrease adaptation effort. Increases in the scale of the world economy or emission intensity boost both types of effort, although more so for mitigation. An increase in the natural regeneration rate necessarily alleviates the need for adaptation or mitigation. A higher discount rate (greater preference for consumption today) reduces mitigation effort, but not adaptation effort. This makes intuitive sense as mitigation involves a trade-off between current and future consumption, whereas adaptation effort does not involve inter-temporal trade-offs.

Again the most interesting results concern the climate change parameters. Unsurprisingly, an increase in the worst case damage from climate change increases both types of effort. Climate change rapidity has not much influence on either abatement or mitigation effort; its effect is either statistically insignificant or weak. An increase in the criticality threshold has little effect on adaptation effort, but reduces mitigation effort. The intuition for this effect is that as the likelihood of climate change recedes with a higher criticality threshold, less mitigation will suffice to prevent crossing the criticality threshold.

**Proposition 4** *The rapidity of climate change has no discernible effect on either adaptation effort or mitigation effort, while an increase in the criticality threshold reduces mitigation effort while leaving abatement effort virtually unchanged.*

## 6 Transitory Dynamics

While the steady state solution is of primary interest, the transitory dynamics of the model provide a few additional insights about the path towards the steady state. The numerical simulations had shown that the mixed adaptation-mitigation regime is unlikely to occur in steady state, and therefore this section will focus only on the adaptation-only and mitigation-only regimes. The dynamics of the system can be described by the time derivatives (indicated by a dot on top of the variable) for the emission concentration and the policy variable. For the mitigation regime, we are interested in $\dot{z}$ and $\dot{m}$, and for the adaptation regime, we are interested in $\dot{z}$ and $\dot{a}$. [8] Obtaining an expression for the motion of emission concentrations is straight-forward. Making use of the steady state solution that yields $z^*$ (and $m^* > 0$ for the mitigation regime), it follows that

$$\dot{z} = \delta \left[ z^* \frac{(1-m)}{(1-m^*)} - z \right] \tag{26}$$

For the adaptation regime, setting $m^* = 0$ yields the appropriate expression.

The dynamics of the mitigation-only regime are characterized by the costate equation (15) and the first-order condition (13) differentiated with respect to time. This results in two equation in an equation for $\dot{m}$:

$$\dot{m} = (\delta + \rho) \left[ \frac{(1-m)(1-M(m))}{\gamma_m + 1 - M(m)} \right] [1 - Z_z(z)\Delta_m(m, z)] \tag{27}$$

with

$$\Delta_m(m, z) \equiv \frac{z^*}{z} \frac{1 - Z(z^*)}{1 - Z(z)} \frac{1-m}{1-m^*} \frac{1 - M(m)}{1 - M(m^*)} \tag{28}$$

For the adaptation-only regime,

$$\dot{a} = \delta\eta(z) \left[ \frac{z^*}{z} - 1 \right] \left[ \frac{(1-a)}{\Delta_a(a, z) + (1-a)Z(z)} \right] \tag{29}$$

with

$$\Delta_a(a, z) \equiv \left[ \frac{(1-a^*)Z(z^*)}{1 - (1-a^*)Z(z^*)} \right] \left[ \frac{1 - (1-a)Z(z)}{(1-a)Z(z)} \right] \tag{30}$$

Perhaps the key insights from equations (27) and (29) is that effort's speed is governed by $\delta + \rho$ and $\delta$, respectively. Everything else equal, a higher time discount rate will speed up the mitigation transition and move quicker from zero effort to steady-state effort. The lower $\rho$, the more drawn-out the transition process becomes.

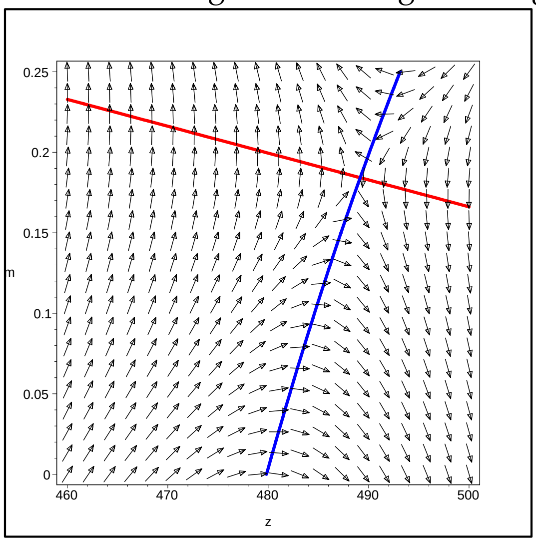
Numerical simulations reveal a fair bit about the transition dynamics. It becomes apparent that the transition state is usually quite short: adaptation and mitigation effort kicks in at an emission concentration level close to the steady-state

[8] For the closed-form expressions below, logarithmic utility ($\alpha = 1$) is assumed.

level and then ratchets up quickly. This is quite true for adaptation, although in the case of mitigation the process may get drawn out by a low time discount rate, as equation (27) suggests.

Figure 5 depicts a typical phase diagram for the mitigation regime. The steady state exhibits saddle-path stability: there exists a single optimal path to the steady state. Deviations from the path will be corrected by immediate and appropriate adjustments in mitigation or adaptation effort.

Figure 5: Phase Diagram for Mitigation Regime




## 7 Uncertainty about Climate Change

With the logistic functional form (5), the basic model outlined above introduced three parameters: the upper damage level ($\bar{Z}$), the climate change rapidity parameter $\omega$ that captures the non-linearity of the process, and the critical threshold $\hat{z}$ that pinpoints where climate change is the most rapid. It does not require much imagination to rank the level of uncertainty surrounding the parameters. Worst-case scenarios will put an upper limit on $\bar{Z}$. The rapidity of climate change is much debated, but climate models put a relatively short time span on major events such as Thermohaline Current collapse. Most controversy (and uncertainty) surrounds the criticality threshold $\hat{z}$, although $\omega$ is also crucially important.

As was shown earlier, the steady-state damage elasticity $\eta(z^*)$ determines whether to adopt an adaptation and/or mitigation policy. However, this damage elasticity is essentially a conjecture based on assumptions about $\hat{z}$ and $\omega$. This means that the ex-ante $\eta(z^*)$ is subject to ex-post error. Assume that the ex-post (true) critical threshold is measured as $\hat{z}^T$, and the corresponding rapidity as $\omega^T$. (The superscripts $^T$ indicate "true".) Then the conjecture error is given by

$$\varepsilon = \ln\left(\frac{\eta(z^*)}{\eta^T(z^*)}\right) = \left[\ln\left(\frac{\omega}{\omega^T}\right) - \ln\left(\frac{\hat{z}}{\hat{z}^T}\right)\right] + \ln(\nu) \tag{31}$$

where $\ln(\nu)$ is a second-order term close to zero. Thus $\varepsilon > 0$ if $\omega > \omega^T$ or $\hat{z} < \hat{z}^T$. Note that expression (31) does not depend on the mismeasurement of the damage ceiling $\bar{Z}/\bar{Z}^T$; this error has no bearing on the decision whether to adopt mitigation or adaptation, but conditional on this choice it will influence the effort level and result either in too little or too much effort. The insights from (31) suggest the following

**Proposition 5** *If the policy maker errs and assumes either*

1. *a critical climate change threshold that is too high ($\hat{z} > \hat{z}^T$), or*
2. *a climate change rapidity that is too "flat" and low ($\omega < \omega^T$)*

*then the ex-ante conjecture of the steady-state damage elasticities will lie below the ex-post (true) steady-state damage elasticities so that $\eta(z^*) < \eta^T(z^*)$. For a given cost factor $\Gamma$ this will bias the policy decision away from mitigation and towards adaptation.*

# 8 The Two-Country Case

To broaden the analysis, consider the case of two countries, home (H) and foreign (F). Empirically, the parameters of interest are the size of the two economies ($y^H$ and $y^F$); the carbon intensity of the two economies ($\kappa^H$ and $\kappa^F$); the maximum damage from climate change ($Z^H$ and $Z^F$); the cost of mitigation ($\gamma_m^H$ and $\gamma_m^F$); and the cost of adaptation ($\gamma_a^H$ and $\gamma_A^F$). The remaining parameters are assumed to be identical across countries (time preference) or are identical by definition (climate change rapidity, climate change threshold).

## 8.1 Theory

The analysis below explores the non-cooperative equilibrium. The cooperative equilibrium is usually the first-best solution, and usually (pareto-)dominates the non-cooperative (strategic) equilibrium. In the cooperative case, country heterogeneity matters primarily for the distribution of effort. However, in the non-cooperative case, country heterogeneity affects the policy choice—and this is ultimately more interesting.

With two countries, each country's GHG emissions are $e^i = \kappa^i y^i (1 - m_i)$ with $i \in \{H, F\}$. World emissions are $e = e^H + e^F$. Further let $\theta \equiv e^H/(e^H + e^F)$ denote the (ex-post) emission share of the home country, which strategically is the conjecture of home country's own emission contribution conditional on the foreign country's policy. Then the change in the level of GHGs is determined by the joint emissions: $\dot{z} = e^H + e^F - \delta z$ From this it follows immediately that steady state emissions are given by

$$z^* = \frac{\kappa^H y^H (1 - m_H^*)}{\delta \theta} \tag{32}$$

This result changes the constraints that define the policy choice of each country. For the adaptation-only regime, $\Gamma \geq \theta \eta(z_{m=0}^*)$, and for the mitigation-only regime,

$\Gamma \leq \theta\eta(z^*_{a=0})$. In case of a mixed policy regime, $\theta\eta(z^*) = \Gamma$. The optimal mitigation effort $m^*_{a=0}$ changes equation (23) equivalently:

$$1 - M(m^*_{a=0}) = \gamma_m \left[1 + \frac{\rho}{\delta}\right] \left[\frac{1 - Z(z^*)}{Z(z^*)}\right] \frac{1}{\theta\,\eta(z^*)} \tag{33}$$

However, in the adaptation-only regime the equation for the optimal $a^*_{m=0}$ remains unchanged.

The presence of a foreign country raises two questions. First, how does the foreign country affect the choice of policy? Second, how does the foreign country affect the optimal effort level for adaptation or mitigation? As the numerical simulations have suggested that mixed policy regimes are unlikely in steady state, the analysis below focuses only on pure strategies.

The boundaries for regime choice change through the introduction of the emission share $\theta$. Smaller countries will tend to have a lower emission share $\theta$, and thus as $\theta$ decreases, it becomes more and more likely that the condition $\Gamma \geq \theta\eta(z^*_{m=0})$ will be satisfied. This is clearly true if the foreign country is also pursuing adaptation, as $\eta(z^*_{m=0})$ will remain the same. Only when the foreign country is relatively large and pursues a mitigation policy, there is a chance that $\eta(z^*)$ increases when the no-policy steady state is to the right of the damage elasticity maximum, i.e., $z^0 > \tilde{z}$. To summarize:

**Proposition 6** *A low emission country (a country with a small economy or low emission intensity) is more likely to pursue an adaptation policy than a high emission country, unless the foreign country pursues a strong mitigation policy.*

How does the emission share $\theta$ affect the adoption of a mitigation policy? As the emission share increases, it becomes more likely that the condition $\Gamma \leq \theta\eta(z^*_{a=0})$ is met. In particular, when $z^0 > \tilde{z}$, mitigation will also increase $z^*_{a=0}$, the more so for a large country that can mitigate more emissions. To summarize:

**Proposition 7** *A large emission country (a country with a large economy or high emission intensity) is unambiguously more likely to pursue a mitigation policy than a small emission country.*

This last proposition is very much in line with results from static models, see for example Farnham and Kennedy (2010). Larger countries mitigate more than smaller countries not only in absolute terms but also in relative terms.

If the home country pursues an adaptation policy, not much changes. If the foreign country also pursues an adaptation policy, nothing changes at all, but if the foreign country adopts mitigation, the steady-state emission concentration $z^*$ will be lower, and the home country enjoys the benefit of the foreign country's actions. These benefits will obviously be larger if the foreign country is larger.

If the home country pursues a mitigation policy, its choice of optimal effort $m^*$ will be affected by the foreign country's policy. If the foreign country adopts an adaptation regime, more mitigation effort is required to achieve reductions in the steady state emission concentration level $z^*$. If the foreign country adopts a mitigation regime, the home country's effort depends on the foreign country's effort. This in turn will be determined by differences in the cost parameter $\Gamma$ for the two countries. Table 6 summarizes the findings for all four cases.

Table 6: Two-Country Policy Regimes: Effect on Home Country

| Home Country | Foreign Country | |
|---|---|---|
| | **Adaptation** | **Mitigation** |
| **Adaptation** | no change | reduced adaptation effort |
| **Mitigation** | enhanced mitigation effort | ambiguous |

Assume that both countries are identical except for the size of their emissions. The case where both countries engage in mitigation requires that $\Gamma \leq \min\{\theta, 1-\theta\}\eta(z^*_{a=0})$. The expression on the right hand side is smallest when $\theta = 1/2$ and the countries are equal in size.

**Proposition 8** *Homogeneity across countries in terms of emission volume makes them more likely to adopt joint mitigation; emission volume heterogeneity makes it less likely to adopt joint mitigation.*

If both countries adopt a mitigation strategy, the resulting non-cooperative equilibrium can be characterized by the mitigation cost ratio

$$\frac{M^F(m^F)}{M^H(m^H)} = \frac{\kappa^H y^H(1-m^F)}{\kappa^F y^F(1-m^F)} \left[\frac{\gamma_m^F}{\gamma_m^H}\right] \frac{Z^H(z^*)/(1-Z^H(z^*))}{Z^F(z^*)/(1-Z^F(z^*))} \tag{34}$$

Both left side and right side of equation (34) depend on $m^F$ and $m^H$ in a non-linear fashion so that a closed form strategic "reaction function" cannot be obtained. However, for the purposes of numerical simulation, equation (34) can be log-linearized and is rather suggestive of how the ratio $m^F/m^H$ depends on other key ratios such as the relative size of the economies $y^H/y^F$.

## 8.2 Simulation Results

The special case where both countries adopt a mitigation strategy is particularly interesting to explore numerically through a further simulation approach. The focus in this case is on the two country's mitigation effort ratio $m^F/m^H$.

Numerical simulations reveal that joint mitigation effort is far less common in a two-country world than in a single-country world, consistent with the theoretical analysis above. In less than 7% of the simulation scenarios do both countries adopt mitigation. The scenario where one country mitigates and the other country adapts is far more common. To analyze the relative mitigation effort level, the results from the simulation run are estimated through

$$\ln\left[\frac{m^F}{m^H}\right] = \beta_0 + \sum_i \beta_i^v \ln\left[\frac{v_i^F}{v_i^H}\right] + \sum_i \beta_i^w \ln\left[\frac{w_i}{w_i^{\text{mean}}}\right] + \epsilon \tag{35}$$

Table 7: Simulation Results: Mitigation Effort Ratio $\Xi$

| Parameter | Symbol | (1) | (2) |
|---|---|---|---|
| intercept | | $0.011$ $(0.031)$ | $0.006$ $(0.033)$ |
| economic size ratio | $\ln(y^F/y^H)$ | $3.023^c$ $(0.079)$ | $3.024^c$ $(0.080)$ |
| emission intensity ratio | $\ln(\kappa^F/\kappa^H)$ | $2.889^c$ $(0.114)$ | $2.892^c$ $(0.115)$ |
| damage ceiling ratio | $\ln(\bar{Z}^F/\bar{Z}^H)$ | $2.980^c$ $(0.102)$ | $2.986^c$ $(0.102)$ |
| mitigation cost ratio | $\ln(\gamma_m^F/\gamma_m^H)$ | $-2.932^c$ $(0.118)$ | $-2.944^c$ $(0.119)$ |
| climate change rapidity | $\ln(\omega/\bar{\omega})$ | | $-0.257$ $(0.133)$ |
| criticality threshold | $\ln(\hat{z}/\hat{z}^{\text{mean}})$ | | $-0.058$ $(0.404)$ |
| regeneration speed | $\ln(\delta/\delta^{\text{mean}})$ | | $0.118$ $(0.449)$ |
| time discount rate | $\ln(\rho/\rho^{\text{mean}})$ | | $0.031$ $(0.082)$ |
| adaptation cost | $\ln(\gamma_a/\gamma_a^{\text{mean}})$ | | $-0.002$ $(0.061)$ |
| world economy size | $\ln(y/y^{\text{mean}})$ | | $-0.144$ $(0.511)$ |
| number of observations | | 678 | 678 |
| regression $R^2$ | | 0.698 | 0.700 |

Note: Standard errors in parentheses. Statistical significance at the 95%, 99%, and 99.9% confidence levels is indicated by the superscripts $^a$, $^b$, and $^c$, respectively. The dependent variable is the log mitigation effort ratio $\Xi$. Regressors are expressed either as the log of a foreign-to-domestic ratio or as the log of a parameter's ratio to its sample mean.

The regressors are logs of either the foreign-to-home ratio of variables that vary across the two countries (e.g., economic size) or the observed-to-mean ratio of variables that are common across the two countries (e.g., climate change rapidity). Even though the estimated relationship is non-linear, the OLS regression provides a good numerical fit. Table 7 shows the results, which can be aptly summarized in the following

**Proposition 9** *The foreign country exhibits a larger mitigation effort than the home country if relative to the home country the foreign country: (i) is larger in size; (ii) is more carbon intensive; (iii) is more exposed to climate change damage; or (iv) faces lower mitigation unit costs.*

Column (1) in table 7 only includes the $v$-type regressors that are different across the two countries, and column (2) in table 7 also includes the $w$-type regressors that are the same across both countries. The results for the first group are very strong, while the results for the second group are insignificant. Only the climate change rapidity paramter is at the border of statistical significance, indicating that as climate change rapidity increases, the effort gap between the two countries decreases.

# 9 Policy Implications and Conclusions

This paper characterizes the dynamically optimal climate change policy mix between mitigation (emission reduction) and adaptation (coping with climate change). A novel feature of this paper involves modeling the non-linearity of climate change explicitly by introducing corresponding parameters for the rapidity of climate change and the criticality threshold. The features of this model are explored through extensive numerical simulations that use a new and innovative sampling technique in combination with the application of conventional econometric tools. Special consideration is given to the problems arising from climate change uncertainty and the presence of two (or more) countries. This paper finds a number of important results regarding the choice between mitigation and adaptation.

1. The adaptation decision for mitigation and adaptation depends crucially on the magnitude of three numbers: an adjusted ratio of mitigation and adaptation cost ($\Gamma$), and the climate change damage elasticity with respect to changes in concentrations of greenhouse gases in the atmosphere with the latter evaluated either at the zero-mitigation or zero-adaptation steady-state level of greenhouse gas concentrations. The four possible regimes (no policy, adaptation only, mitigation only, and a combination of both policies) depends on the interplay of these three numbers.

2. In contrast to a number of earlier studies (Ingham et al., 2005b,a; Tol, 2005; Settle et al., 2007), the model presented here does not suggest that mixing mitigation and adaptation at the world level or country level is optimal. Instead, the mix of adaptation and mitigation will arrive from cross-country heterogeneity in policy adoption.

3. An increase in the criticality threshold will: (i) increase the probability of adopting mitigation rather than adaptation; (ii) increase the probability of not adopting any policy at all; (iii) reduce mitigation effort conditional on adopting such a policy.

4. An increase in climate change rapidity will: (i) increase the probability of adopting mitigation rather than adaptation; (ii) slightly increase the probability of adopting some policy; (iii) have no discernible effect on either abatement or mitigation effort.

5. Climate change uncertainty (criticality threshold, rapidity) biases the policy choice: adaptation becomes more likely when policy makers assume that climate change is "too far out" or more linear than non-linear.

6. With two countries, adaptation becomes more likely overall, and the larger country is more likely to mitigate relative to the small country.

7. Emission volume heterogeneity makes countries less likely to adopt joint mitigation.

What lessons can a policy maker take away from the theoretical and empirical exercise in this paper? Most importantly, the odds are stacked against coordinating on mitigation policies. Small (emission) countries will tend to prefer adaptation over mitigation, which reduces the potential for the efficacy of mitigation. The burden of mitigation policies is squarely put on the shoulders of large emitter nations. And whether they prefer adaptation or mitigation depends heavily on whether their country characteristics bias them towards adopting mitigation in the first place. To complicate things even further, the lack of sufficient precision about the key climate change parameters (criticality threshold, rapidity) may inadvertently bias the policy decision further towards adaptation. The failure of the Copenhagen summit in 2009 to produce a strong internationally-coordinated mitigation program is entirely consistent with this paper's theoretical and empirical results.

# References


Agrawala, Shardul and Frankhauser, Samuel (Eds.) (2008). Economic Aspects of Adaptation to Climate Change: Costs, Benefits and Policy Instruments. Organization for Economic Co-Operation and Development.

Chiang, Alpha C. (1992). Elements of Dynamic Optimization. New York: McGraw-Hill.

Cline, William R. (2007). Global Warming and Agriculture: Impact Estimates by Country. Washington, DC: Peterson Institute.

Farnham, Martin and Kennedy, Peter W. (2010). Equilibrium Climate Policy: Abatement vs. Adaptation, and the Prospects for International Cooperation. University of Victoria, Department of Economics.

Felgenhauer, Tyler and De Bruin, Kelly C. (2009). The optimal paths of climate change mitigation and adaptation under certainty and uncertainty. International Journal of Global Warming, 1(1-3), 66–88.

Ingham, A., Ma, J., and Ulph, A.M. (2005a). Can adaptation and mitigation be complements? Tyndall Centre for Climate Change Research, Report 79.

Ingham, A., Ma, J., and Ulph, A.M. (2005b). How do the costs of adaptation affect optimal mitigation when there is uncertainty, irreversibility, and learning? Tyndall Centre for Climate Change Research, Report 74.

IPCC (2007). Climate Change 2007 Synthesis Report. Geneva: Intergovernmental Panel on Climate Change.

Kane, Sally and Shogren, Jason F. (2000). Linking adaptation and mitigation in climate change policy. Climatic Change, 45, 75–102.

McGranahan, G., Balk, D., and Anderson, B. (2007). The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. Environment and Urbanization, 19(1), 17–37.

Nordhaus, William (2007). Critical Assumptions in the Stern Review on Climate Change. Science, 317, 201–202.

Nordhaus, William and Boyer, J. (2000). Warming the Wolrd: Economics Models of Global Warming. Cambridge,MA: MIT Press.

Schneider, Stephen S. (2004). Abrupt non-linear climate change, irreversibility and surprise. Global Environmental Change, 14, 245–258.

Settle, Chad, Shogren, Jason F., and Kane, Sally (2007). Assessing mitigation-adaptation scenarios for reducing catastrophic climate risk. Climatic Change, 83(4), 443–456.

Shalizi, Zmarak and Lecocq, Franck (2009). To Mitigate or to Adapt: Is that the Question? Observations on an Appropriate Response to the Climate Change Challenge to Development Strategies. The World Bank Research Observer, forthcoming.

Tol, Richard S.J. (2005). Adaptation and mitigation: trade-offs in substance and methods. Environmental Science and Policy, 8, 572–578.

Uzawa, Hirofumi (2003). Economic Theory and Global Warming. Cambridge University Press.

Weitzman, Martin L. (2009). On Modeling and Interpreting The Economics of Catastrophic Climate Change. Review of Economcis and Statistics, 91(1), 1–19.

World Bank EACC Project Team (2009). The Costs to Developing Countries of Adapting to Climate Change: New Methods and Estimates. Technical report, World Bank.

# APPENDIX

## Triangular Distribution

The probability density function of the triangular distribution is given by

$$f(x; L, M, H) = \begin{cases} \dfrac{2(x-L)}{(H-L)(M-L)} & \text{for } L \leq x \leq M \\ \dfrac{2(H-x)}{(H-L)(H-M)} & \text{for } M \leq x \leq H \end{cases}$$

with mean $(L + M + H)/3$ and variance $(L^2 + M^2 + H^2 - LH - LM - MH)/18$, and the cumulative distribution function is given by

$$F(x; L, M, H) = \begin{cases} \dfrac{(x-L)^2}{(H-L)(M-L)} & \text{for } L \leq x \leq M \\ 1 - \dfrac{(H-x)^2}{(H-L)(H-M)} & \text{for } M \leq x \leq H \end{cases}$$

For computational purposes, most statistical software packages provide a function to generate a uniform $[0, 1]$ random variable. To generate a random variate $X$ from the triangular distribution, draw a random variate $U$ from the uniform $[0, 1]$ distribution and calculate

$$X = \begin{cases} L + \sqrt{U(H-L)(M-L)} & \text{for } 0 \leq U \leq F(M) \\ H - \sqrt{(1-U)(H-L)(H-M)} & \text{for } F(M) \leq U \leq 1 \end{cases}$$

where $F(M) = (M - L)/(H - L)$.