

Optimal Technological Portfolios for Climate-Change Policy under Uncertainty: A Computable General Equilibrium Approach*

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ABSTRACT

When exploring solutions to long-term environmental problems such as climate change, it is crucial to understand how the rates and directions of technological change may interact with environmental policies in the presence of uncertainty. This paper analyzes optimal technological portfolios for global carbon emissions reductions in an integrated assessment model of the coupled social-natural system. The model used here is a probabilistic, two-technology extension of Nordhaus' earlier model (Nordhaus and Boyer, 2000) by incorporating endogenous technological choice between conventional and carbon-free technologies. Taking into account the possible competitions among the technological options, we address the issues of optimal timing, costs and burden-sharing of optimal carbon mitigation strategies in the inherently uncertain world. We perform various analyses related to the major uncertainties about natural, socioeconomic and technological parameters, and investigate the effects of uncertainties resolution, risks and alternative political preferences. The results show that analyses ignoring uncertainty could lead to inefficient and biased technology-policy recommendations for the future.

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Key words: Optimal technological portfolios, uncertainty, probabilistic integrated assessment, Monte Carlo experiments, carbon mitigation technologies

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Introduction

Climate change is a long-term, global problem featuring complex interactions between environmental, socioeconomic, and technological processes. Developing a policy response to this problem involves identifying efficient and diverse technological options for global emission reductions required to prevent dangerous anthropogenic interference with the climate system¹, and coping with the enormous layers of uncertainties surrounding the coupled natural-human system.

This paper analyzes the optimal technological portfolios for carbon emissions reductions for a specific environmental goal in a probabilistic integrated assessment (IA) modeling framework. The technological portfolios here refer to what carbon mitigation efforts would occur in the carbon-constrained world, as compared to the business-as-usual world. They are categorized into the two broad groups (or clusters) of carbon mitigation technologies: conventional (fossil-fuel based) versus new (carbon-free) technologies.² Taking into account the competitions between the two highly-stylized technological options, we address the issues of optimal timing, costs and burden-sharing of optimal carbon mitigation strategies in the uncertain world. We then perform various analyses related to the major uncertainties about natural, economic and technological parameters, and investigate the effects of parameter uncertainties, risks and alternative political preferences.

¹ Article 2 of the UN Framework Convention on Climate Change (UNFCCC, 1992) states its ultimate objective as “Stabilization of greenhouse gas concentration in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system.

² A somewhat stylized difference between conventional and new (carbon-free) energy technologies is that the latter are initially much costlier in mitigation than the former, but their costs are assumed to be decrease more rapidly with their diffusions, making the new technologies more competitive (Nakicenovic et al., 1998). In addition, the possibility of a carbon tax biases the technological portfolio more in favor of the new technologies. Note also that technological changes that govern the technological portfolios are inherently dynamic and uncertain in nature.

This paper attempts to quantify the possible future competing roles of alternative carbon mitigation options for preventing dangerous anthropogenic interference with the climate system (e.g., stabilizing climate) in the uncertain environments. Since the problems of choosing cost-efficient energy technologies are ones of scarcity and choice, appropriate response strategies that capture this behavior are intertemporal optimization techniques in the framework of dynamic general equilibrium.

The primary goal of this paper is to expand the existing integrated assessment (IA) modeling capabilities by incorporating endogenous technological choice and the diffusion of innovative technologies under a variety of uncertainties, so that climate-change policymakers can gain clear insights into future energy technology strategies. Specifically, this new modeling approach is used to explore the potential competitions (or trade-offs) between carbon mitigation technologies as a function of scenarios, assumptions or uncertainties as well as of various environmental goals. To do this, we develop a simple prototype technology-choice model of integrated assessment that incorporates a highly-stylized bottom-up cost information and technical progress components for the two grouped technology clusters under considerable parameter uncertainty about geophysical, technological, and socioeconomic processes. Despite its high-level abstractions, the uncertainty analyses can provide us with a better understanding for sources and management of technology-dependent domains of innovation and competition and their interactions with the environment.

By using the probabilistic, two-technology extension of the recent Nordhaus model (Nordhaus and Boyer, 2000) of the economics of global warming, we investigate the implications of endogenous technological change and choice for alternative carbon mitigation options (carbon and non-carbon energy technologies) in the presence of uncertainty. While maximizing discounted per capita consumption by controlling capital investment and two types of carbon mitigation options, the analysis captures the

potential for possible mitigation technologies, taking into account endogenous technological progress, competition and diffusion.

The main question addressed in this paper includes the effects of layers of uncertainty on the optimal technological portfolios for climate-change policy in the presence of a policy-important climate threshold. Unlike many previous studies relying on a limited set of scenarios or deterministic outcomes, the probabilistic integrated assessment approach employed here allows us to explore optimal technological portfolios in a dynamic general equilibrium setting (based on embedded, quantitative descriptions of uncertainties). The paper provides some metrics for assessing the potentials for having dangerous global warming, for exceeding critical levels of policy-relevant regrets, or for having dominant mitigation technologies as a function of scientific and socioeconomic uncertainties. It also examines the ranges of economic value of resolving scientific uncertainties about climate change early rather than late, depending upon technological and environmental constraints.³

The Model

The main building block of the model used here is the well-known Nordhaus' Dynamic Integrated Climate and Economy (DICE) model (Nordhaus and Boyer, 2000) that is an optimal growth model of the world economy including future CO₂ emissions, concentration and global mean temperature dynamics from economic activity. This paper extends the DICE model of climate change policy to incorporate possible competitions between two broad groups of carbon mitigation options in a probabilistic framework. In particular, it captures endogenous links between climate policy and the direction and composition of future technological innovations to solve the global warming problem.

³ Note that the value of early knowledge information can be extremely large to the extent that man-made investments and efforts are expensive and the stringency of policy goal is non-negligible.

The economy produces a single final good. Individual utility depends on consumption of the final good and on the quality of the environment (e.g., global mean temperature). The environmental quality can be augmented by reductions in carbon emissions via conventional mitigation technology (e.g., policy-induced efficiency improvement and substitution into less carbon-emitting fossil fuel sources) or via the supply of new carbon-free alternatives (e.g., non-carbon activities such as backstop-like or renewables).

Economic activity is described by a production function and uses of output. Output at time t , $Y(t)$, depends on the inputs of labor $L(t)$, general physical capital $K_C(t)$:

$$Y(t) = \Omega(D(t))K_C(t)^\gamma (A(t)L(t))^{1-\gamma} = C(t) + I(t) + I_\mu(t) + I_\zeta(t), \quad (1)$$

where $A(t)$, labor productivity, is assumed to increase with decreasing rate over time following $A(t) = [1 + g_A(t)]A(t-1)$. Labor is supplied inelastically, and is determined by exogenous population growth (with its rate of decline δ_L) and capital stock is accumulated in the usual fashion. Output (net of climate damage $D(t)$) is available for private consumption $C(t)$, private investment $I(t)$, and the two forms of carbon mitigation efforts including investments in conventional technology $I_\mu(t)$ and carbon-free technology $I_\zeta(t)$. Similar to a physical general capital, these energy-specific knowledge/experience stocks are assumed to be generated by the accumulation of previous efforts:

$$K_i(t) = I_i(t) + (1 - \delta_i)K_i(t-1), \quad i = c, \mu, \text{ and } \zeta. \quad (2)$$

In the model, emissions from burning fossil fuels are identified as carbon, and they can be reduced either by the direct carbon abatement effort $\mu(t)$ or the indirect supply effort of non-carbon activities $\zeta(t)$. The carbon emissions are thus written as

$$E(t) = \sigma(t)[1 - \mu(t) - \zeta(t)]Y(t), \quad (3)$$

where $\sigma(t)$, the business-as-usual carbon emissions intensity of production, is regarded as declining exogenously with decreasing rate over time due to “autonomous energy-efficiency improvement” (AEEI) following $\sigma(t) = \sigma(t-1)/[1 + g_\sigma(t)]$.

On the other hand, the cost of each of the “direct” carbon mitigation options, $\mu(t)$ and $\zeta(t)$ in terms of output is assumed to be

$$I_i(t) = c_{0i} [K_i(t)]^{-\alpha_i} [i(t)]^{c_{1i}} Y(t), \quad \text{where } i(t) = \mu(t) \text{ and } \zeta(t), \quad (4)$$

respectively and where c_{0i} is a normalization parameter and α_i is the learning elasticity index (Messner, 1997; Anderson, 1999). It is assumed that the technological progress is also represented as a decreasing function of cumulative installed capacity and pertains to investment costs for each of the technologies. Note that the accumulation of knowledge here occurs in part not as a result of direct deliberate efforts, but as a side effect of conventional economic activity. This type of knowledge accumulation is known as “learning-by-doing” (Arrow, 1962) and its simplest case is when the learning occurs as a side effect of the production of new capital (Romer, 1996, pp.116-117).⁴ At each point in time t , given accumulated knowledge stocks, the economy determines the optimal portfolio for the mitigation options under a specific environmental goal. The optimal portfolios are now a function of scenarios, environmental goals, and assumptions on uncertain model parameters.

In the economy, the dynamic equilibrium path of the coupled natural-human system is characterized as the solution to an optimization problem, maximizing discounted utility of per capita consumption subject to economic and environmental resource constraint and several policy instruments. There are three controls in the model: the rate

⁴ As is typical in the endogenous growth literature, the stock of knowledge can be formulated as a usual power function of the stock of capital, since the increase in knowledge is a function of the increase in capital.

of physical investment $I(t)$, the rate of direct carbon-emissions mitigation options $\mu(t)$ and the rate of supply for non-carbon activities $\zeta(t)$. Note that the model outcomes are dependent on the choice of the uncertain parameter values and their probability distributions and, in particular, that most of the parameters needed to model endogenous technological change and choice are also subject to considerable uncertainty. Moreover, in the real world, evolution of technologies will also include technologies potentially developed in the future.

Elements of uncertainties and the way of propagating uncertainties throughout the model could affect significantly the optimal technological portfolios (and their policy implications), and it would be desirable to take into account this factor when reporting the model outcomes. Thus, desirable advice based on such a model outcome is not in the form “if society sets its environmental goal in this way, then the outcome will be as follows,” but rather “if society sets its environmental goal in this way, then the outcomes will be within the ranges shown.” Moreover, as knowledge about the uncertainties improves, our decisions and responses can be more focused and potentially wasteful decisions can be avoided significantly.

Since our model uses the Nordhaus and Boyer (2000)’s global model as its basic macroeconomic block, coefficients already present in the original model are left unchanged. For new parameter calibration, we need to identify all possible underlying technological options, while representing their technological changes over time that become important in the carbon-constrained cases. To this end, we follow the relevant literature to adopt plausible parameters values for the dynamics of the energy-economic system against future global warming and the dynamic link between carbon concentration and temperature increase. The assumptions on the new technology parameters and their plausible ranges are made from some of the previous studies including McDonald and Schrattenholzer (2001), Popp (2002), Gerlagh and Lise (2003)

and Sims et al. (2003).⁵ However, note that in general, no good empirical estimates exist for this kind of technological parameters due to the lack of sufficient, empirical data. As Weyant (1997) emphasizes, there do not exist single, established information on most of the uncertain technological parameters on this calibration issue. Obtaining good empirical estimates for these parameters is one of the most difficult challenges of dealing with endogenous and induced technological change, and the analysis can be improved further as we get more technological information and experience later. For the key uncertain climate parameter, we refer to several previous studies, surveyed in Dessai and Hulme (2003). Assumptions on the plausible distributions for all other uncertain variables are adopted from Norhaus (1994), Nordhaus and Popp (1996), and Pizer (1997), etc.

Results and Discussions

Based on seven recent studies on the plausible distributions estimates for the climate sensitivity parameter, Fig. 1(a) derives a simple, averaged synthesis (thick blue solid line) approximated by log-normal probability distribution.⁶ Fig. 1(b) displays the corresponding cumulative probability distribution adopted for our present study, which yields 10th, 50th, and 90th percentile for climate sensitivities of 1.5 °C, 2.8 °C, and 5.2 °C, respectively.

⁵ The global general R&D by OECD countries is \$500 billion and, for US, 2% of R&D expenditure is for energy technology (= \$10 bil.) (Popp, 2002). According to Popp (2002) and Anderson (1997), the R&D investment in backstops is assumed to be about 1/10 of that of the conventional energy technologies in the base year. So, for the initial knowledge stocks of conventional and new technologies, we assume US \$10 billion and US \$1 billion, respectively. Following Gerlagh and Lise (2003) and Sims et al. (2003), the initial cost for new carbon-free technology is assumed to be 4 - 5 times (or \$400 - 500/tC avoided) higher than conventional technology. Also, McDonald and Schrattenholzer (2001) present a range of 8 - 30% learning rate for a large set of new energy technologies at large.

⁶ “Climate sensitivity” here is defined as the equilibrium global-mean temperature change in response to a doubling of CO₂ concentrations. Note that most of these recent studies produce distributions wider than the IPCC range (1.5 - 4.5°C).

Fig. 2 displays band estimation for carbon emissions, global warming and technology choice over time for two scenarios: BAU vs. WAIS. In Fig. 2(a) and (b), BAU represents “no policy” and WAIS is “2.5 °C temperature stabilization policy.”⁷ Shown are the estimated probabilistic ranges for (a) global carbon emissions, (b) global mean temperature increase, and (c) carbon mitigation technology portfolio over time. Lower and upper dashed lines in each panel refer to 1st quartile and 3rd quartile values in the distribution for each variable, respectively. In Fig. 2(c), note that MIU refers to “conventional technologies” and ZETA refers to “carbon-free technologies” (i.e., renewables and backstops approximately including solar/wind powers, carbon sequestration, hydrogen, biomass, etc.) under the WAIS case. Under the climate constraint scenario chosen, we can see in Fig. 2(c) that carbon-free technologies would play an important role for carbon emission reductions over the 21st century (with wider variances in the middle of the century), which portrays a substantial acceleration in the transition of the energy system to non-fossil-fuel energy sources in comparison to the BAU reference scenario.

We investigate the distribution of the economic effects of WAIS policy under alternative scenarios that are crucially subject to conjectural forces affecting generic productivity growth and autonomous energy-efficiency. Note that, in general, the cost and performance of carbon mitigation polices depend crucially on the evolution of labor productivity (A), which is a major determinant for the future economic growth, and the evolution of autonomous energy-efficiency improvement (σ). We consider four alternative scenarios about uncertain future economic environments, distinguished by the assumptions on the evolutions of two fundamental parameters, $g_A(t)$ and $g_\sigma(t)$ that would dominate various economic and technological environments for the technological

⁷ For a specific environmental goal to avoid dangerous anthropogenic interference in this paper, we consider technology policies designed to limit the globally-averaged warming below 2.5°C that has been suggested as the temperature at which a collapse of the West Antarctic Ice Sheet (WAIS) might occur. For a detail on this issue, see Oppenheimer (1998).

portfolios. Our scenarios with four different states-of-the-world are named and classified according to the main assumptions surrounding a plausible range of future economic activity and technological changes in energy technologies. In Fig. 3, “Central” scenario assumes the case with reference labor productivity growth (= 1.4% /yr) and reference AEEI growth (= 1.3% /yr), based on the historical trends. The extreme cases here are assumed as follows: (i) “HH” case is with *higher* labor productivity growth (= 2.5% /yr) and *higher* AEEI growth (= 2.2%/yr), (ii) “HL” case is with *higher* labor productivity growth (= 2.5% /yr) and *lower* AEEI growth (= 0.5%/yr), (iii) “LH” case is with *lower* labor productivity growth (= 0.8% /yr) and *higher* AEEI growth (= 2.2%/yr), and (iv) “LL” case is with *lower* labor productivity growth (=0.8% /yr) and *lower* AEEI growth (= 0.5%/yr). In Fig. 3(a), the “WAIS wedge” is defined as the gap between carbon emissions of BAU and WAIS in a specific year.

In relation to the timing and costs of carbon emission reductions, we next analyze the economic implications of “procrastinating” optimal climate policies designed to limit the globally averaged warming below 2.5°C. In Fig. 4, we present the probabilistic assessments of “regrets” as a function of procrastination. The “regrets” defined here, as a social cost of procrastination, is approximated by the net present value of the future consumption losses of optimal policies with each specific procrastination constraint (*i.e.*, no carbon control for a certain number of years), relative to without procrastination activities (*i.e.*, ‘act now’ policy for the WAIS). It is shown that the endogenously-calculated possibility and risk of probabilistic “regrets” can increase substantially with the years of procrastination. Note here that x-axis is logarithmic.

In addition, Fig. 5 shows the modeled relationship between the procrastination period and the probability of exceeding “critical level of regrets (CR)”. The solid lines indicate the probability of having outcomes above the stated threshold of critical regrets

for the policymaker for any given level of years of procrastination. For example, with a relatively high value of CR (= 10%) of 2003 global GDP chosen, the probability of “regrets” exceeding a range of CR values increases from near 0% with 30 years of procrastination to almost 75% with 60 years of procrastination. In particular, it is revealed that for most of a plausible range of CR values, the endogenously-determined, possible risks and economic consequences of procrastination (in terms of economic burden) would go abruptly severe just within 30 - 60 years.

Fig. 6 displays the distribution of probabilistic “regrets” under alternative economic and natural circumstances. Shown are the distributions of possible regrets for the WAIS case, depending on some alternative assumptions about future economic activity (labor productivity growth), future technological improvement in energy technologies (AEEI growth), and tighter climate threshold (= 2 °C temperature limit). As we would expect, the possible regrets rises with the higher labor productivity growth and falls with optimistic AEEI growth in a significant manner. In addition to these major uncertain economic parameters, the probabilistic range of regrets increases greatly with a tighter climate threshold.

The probability of exceeding critical level of “regrets” is shown as a function of major uncertain economic and natural assumptions in Fig. 7. With 30 years of delay in WAIS policy, Fig. 7(a) and (b) display the probability of having dangerous regrets above 5% of 2003 GWP and above 10% of 2003 GWP, respectively. As indicated in the figures, more optimistic energy technology reduces significantly the possibility of the outcome’s exceeding the stated burden thresholds, compared to the central case. On the contrary, it is shown that labor productivity enhancement (a proxy for general economic productivity growth, but ‘without’ AEEI improvement) or, more seriously, a tighter climate threshold (2°C limit) calls for more risky treatments of procrastination

policy and its regrets implications. In either case, the amount of wealth needed to compensate for the lost opportunity due to procrastination can increase significantly.

To see the effects of the scope of uncertainty on model outcomes, Fig. 8 simulates the distribution of the WAIS wedge in 2035 under alternative scope of parameter uncertainty in the model. The “wedge” here is defined as the required gap between carbon emissions of BAU and WAIS in a specific year, which in turn determines the degree of policy stringency. This figure compares the required wedges in 2035 “with only climate sensitivity uncertain” (dashed line) to “with all parameters uncertain” (solid line). In most cases, the estimates for all other uncertain economic parameters (except for our climate sensitivity) are drawn from the relevant literature (Nordhaus, 1994; Nordhaus and Popp, 1997; Pizer, 1999). As implied in the literature, ignoring more uncertainty tends to lower the stringency of optimal policy. For example, the result indicates that, relative to the natural parameter uncertainty only (i.e., climate sensitivity), considering additional uncertainties surrounding other economic parameters into the model increases the median (50th percentile) wedge value by about 30%.

Fig. 9 compares the estimates for the distribution of carbon mitigation technologies: conventional versus carbon-free technology. Shown in the left and right panels are the distributions of efficient choice of carbon mitigation technologies under the WAIS in 2035 and in 2075, respectively. For each technology, the dashed line refers to the outcomes from “with only climate sensitivity uncertain” case, and the solid line from “with all parameters uncertain” case.

Fig. 10 displays the sensitivity of the median WAIS “wedge” value in 2035 to various uncertain model parameters: (a) rate of population growth decline, (b) scaling factor of labor productivity growth, (c) scaling factor of AEEI growth, (d) technological

learning rate, and (e) pure rate of time preference. In Fig. 11, we also explore the sensitivity of probability of BAU global warming in 2105 exceeding 2.5 °C with respect to the same model parameters.

To shed some light on the relative importance of future technological options under uncertainty, we compare the estimates and possibilities distributions for the two technological options under various situations. First, Fig.12a-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the uncertain rate of future population growth decline. (Note that MIU35 refers to “conventional technology” and ZETA35 refers to “carbon-free technology” in 2035.) Fig.12a-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *decreases* with the rate of population growth decline.

The results of the same sensitivities to the major uncertain economic parameters about the trends of future labor productivity and AEEI growth are shown in Fig.12b and Fig.12c. The left panels in the figures depict how the optimal median technological portfolio values for MIU and ZETA respond to the degree of uncertain future labor productivity growth and to the degree of uncertain future AEEI growth, respectively. The results imply that the probability of ZETA’s exceeding MIU *increases* with the labor productivity growth (Fig.12b-ii], whereas it *decreases* with AEEI growth (Fig.12c-ii).

Fig.12d-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the uncertain technological learning rate for ZETA. Note that, as expected, we can see that the median fraction of ZETA mitigation effort rises exponentially with the learning rate. Fig.12d-(ii) indicates that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *increases* with the technological learning rate for ZETA.

The same analysis with respect to the uncertain pure rate of time preference are shown in Fig.12e. The left panel implies that the optimal median technological portfolio values for ZETA is highly responsive to the uncertain pure rate of time preference. Moreover, the right panel shows that the chance of ZETA's dominance in the role of carbon mitigation *decreases* greatly with the society's pure rate of time preference.

Finally, we examine the effects of learning about uncertainty, hedging and estimate the value of early information. The decisions are made in light of currently available information and they reflect the range of possible outcomes given the degree of uncertainty and risk aversion. Figure 13(a) and (b) show the effects of learning about uncertain climate sensitivity in 2065 (compared to late learning) on optimal mitigation policies, MIU and ZETA, respectively. We assume equal probability of three true state of the world about climate sensitivity. Note that before learning in 2065, policies cannot be state-contingent, and thus are equal in all state of the world. Uncertainty raises optimal level for each of the technology policies significantly.

Fig. 14 estimates the value of scientific knowledge about the climate sensitivity variables depending upon the year in which uncertainties are revealed. Here we compare the present value of increased utility of consumptions for each case relative to the case where perfect information is attained in 2085 across alternative environments about the technological learning rate and the climate threshold. The results imply that the value of early information can be highly dependent upon how fast the uncertainty will narrow over time and that it can be extremely large with pessimistic technological progress and tighter environmental goals, and *vice versa*.

Extensions

Using a new and highly stylized integrated assessment model of technology choice, this paper presents probabilistic integrated assessments and uncertainty analyses of optimal timing, costs and technology choice of carbon emission reductions in a carbon-constrained world. The key feature of the model developed here includes its dynamic general equilibrium nature to incorporate various uncertainties and information about geophysical, technological and socioeconomic processes, along with the capacity to search for optimal technological portfolios against global warming problem.

Uncertainty analysis with the simple integrated assessment model reveals that the endogenous technological portfolios are highly dependent on assumptions about the plausible range of uncertainties surrounding climate, technological and socioeconomic parameters and the stringency of the society's environmental goals. Moreover, the results imply that analyses ignoring this considerable uncertainty could lead to inefficient and biased technology-policy recommendations for the future.

We keep the underlying technology-choice model of the integrated assessment processes as simple as possible for its transparency and tractability. The probabilistic and risk-management framework used for this study can be applied to all levels of model complexity and high dimensionality of the problem. The present work can also be extended further to include: (i) an endogenous technological portfolio component with emphasis on international technology spillovers, (ii) more diversification of technological portfolios (e.g., “demand-side” efficiency technologies as well as “supply-side” technologies) to combat climate change, and (iii) a state-of-the-art combination of the two traditions of endogenizing technological change via both R&D (learning-by-searching) and LBD (learning-by-doing) in the stochastic integrated assessment model (as in Appendix C). Based on the availability for reliable data and parameter calibration in this direction, it would be useful to analyze the competition

between carbon mitigation technologies in the presence of multi-regional, technological spillovers and catch-ups, and trade of carbon permits, which is left for future research.

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Appendix A: Equations of the model

This technical appendix A presents the complete equations of the simple state-contingent model of endogenous technological change and choice for climate-change policy.

Sets: t = time periods (0 to 40)

i (subset) = two broad, stylized categories of mitigation options
(μ = conventional, ζ = carbon-free)

1. Equations of the model:

Utility

$$W = E_0 \sum_t \left[\frac{1}{1 + \rho(t)} \right]^t L(t) \ln [C(t) / L(t)] \quad (\text{A1})$$

Economic and technological constraints

$$Y(t) = \Omega(D(t)) K_C(t)^\gamma (A(t)L(t))^{1-\gamma} = C(t) + I(t) + I_\mu(t) + I_\zeta(t) \quad (\text{A2})$$

$$\text{where } \Omega(D(t)) = 1 / [1 + D(t)] = 1 / [1 + d_1 T(t) + d_2 T(t)^{d_3}]$$

$$K_i(t) = I_i(t) + (1 - \delta_i) K_i(t-1), \quad i = c, \mu, \zeta \quad (\text{A3})$$

$$E(t) = \sigma(t) [1 - \mu(t) - \zeta(t)] Y(t) \quad (\text{A4})$$

$$I_i(t) = c_{0i} [K_i(t)]^{-\alpha_i} [i(t)]^{c_{1i}} Y(t), \quad i = \mu, \zeta \quad (\text{A5})$$

Stochastic processes on generic productivities

$$A(t) = \varphi A(t-1) + (1 - \varphi) A^*(t-1) + \varepsilon_A(t) \quad (\text{A6})$$

$$\sigma(t) = \pi \sigma(t-1) + (1 - \pi) \sigma^*(t-1) + \varepsilon_\sigma(t) \quad (\text{A7})$$

and other uncertain parameters.

Environmental constraints

$$M_{AT}(t) = E(t-1) + a_{11} M_{AT}(t-1) + a_{21} M_{UP}(t-1) \quad (\text{A8})$$

$$M_{UP}(t) = a_{22} M_{UP}(t-1) + a_{12} M_{AT}(t-1) + a_{32} M_{LO}(t-1) \quad (\text{A9})$$

$$M_{LO}(t) = a_{33} M_{LO}(t-1) + a_{23} M_{UP}(t-1) \quad (\text{A10})$$

$$F(t) = 4.1 \ln \left\{ \left[M_{AT}(t) / M_{AT}^{PI}(t) \right] / \ln 2 \right\} + O(t) \quad (\text{A11})$$

where $O(t) = -0.1965 + 0.13465t$, $t < 12$; $= 1.15$, $t \geq 12$

$$T(t) = T(t-1) + \kappa_1 \left\{ F(t) - (4.1/CS)T(t-1) - \kappa_2 [T(t-1) - T_{LO}(t-1)] \right\} \quad (\text{A12})$$

$$T_{LO}(t) = T_{LO}(t-1) + \kappa_3 \left\{ T(t-1) - T_{LO}(t-1) \right\} \quad (\text{A13})$$

2. Parameters: adopted mostly from Nordhaus and Boyer (2002), except for the assumptions on the technological and climate parameters and their plausible ranges made from Sims et al. (2003), McDonald and Schrattenholzer (2001), and Dessai and Hulme (2003). Assumptions on the probability distributions for all other uncertain variables are adopted from Nordhaus(1994), Nordhaus and Popp(1996), and Pizer (1997), etc.

α_μ	Technological learning index (or progress ratio) for MIU	/ .0816/
α_ζ	Technological learning index (or progress ratio) for ZETA	/ .7515/
$c_{0\mu}$	Scaling parameter for cost curve of MIU technology	/ .045/
$c_{1\mu}$	Exponent parameter for cost curve of MIU technology	/ 2.15/
$c_{0\zeta}$	Scaling parameter for cost curve of ZETA technology	/ .180/
$c_{1\zeta}$	Exponent parameter for cost curve of ZETA technology	/ 1/
ρ	Initial rate of social time preference per year	/ .03/
A	Level of total factor productivity	/ .01685/
σ	CO2-equivalent emissions-GNP ratio	/ .272/
δ_i	Depreciation rate for technology i	/ .10/
γ	Capital elasticity in production function	/ .30/
$M_{AT}(0)$	Concentration in atmosphere 1990 (b.t.c.)	/ 735/
$M_{UP}(0)$	Concentration in upper strata 1990 (b.t.c.)	/ 781/
$M_{LO}(0)$	Concentration in lower strata 1990 (b.t.c.)	/ 19230/
a11	Carbon cycle transition matrix	/ .66616/
a12	Carbon cycle transition matrix	/ .33384/
a21	Carbon cycle transition matrix	/ .27607/

a22	Carbon cycle transition matrix	/60897/
a23	Carbon cycle transition matrix	/11496/
a32	Carbon cycle transition matrix	/00422/
a33	Carbon cycle transition matrix	/99578/
$T_{LO}(0)$	1985 lower strat. temp change (C) from 1900	/06/
$T(0)$	1985 atmospheric temp change (C)from 1900	/43/
$K(0)$	1990 value capital trill 1990 US dollars	/47/
κ_1	Speed of adjustment parameter for atm. temperature	/226/
CS	Equilibrium atm temp increase for CO2 doubling (deg C)	/2.8/
κ_2	Coefficient of heat loss from atm to deep oceans	/44/
κ_3	Coefficient of heat gain by deep oceans	/02/
d1	Damage coeff 1	/00071/
d2	Damage coeff 2	/00242/
d3	Exponent of damage function	/2/

Appendix B: Learning rates and unit cost functions

1. (Learning rates) In the basic learning mechanism model, a commonly used learning-by-doing (LBD) component for each technology i is

$$C_i = c_{0i} [K_i(t)]^{-\alpha_i}, \quad i = \mu, \zeta \quad (A5')$$

where c_{0i} is a normalization parameter and α_i is the learning elasticity index. Every doubling of installed capacity ($K_i(t)$) reduces the technology costs (C_i) by a factor of $2^{-\alpha_i}$, which is also called “progress ratio” (PR). The complementary “learning rate” (LR) is $1 - PR = 1 - 2^{-\alpha_i}$, which gives the percentage reduction in the capital investment costs of newly installed capacity for every doubling of cumulative capacity (c.f., Anderson, 1999).

2. (Unit cost function) Estimating unit cost function for each technology i (in the form of a generalized power function as a dual to the Cobb-Douglas production) is

$$\ln \left[\frac{COST_i(t)}{GDP(t)} \right] = \ln c_{0i} + c_{1i} \ln [i(t)] - \alpha_i \ln K_i(t), \quad i = \mu, \zeta. \quad (A5'')$$

Appendix C: Extended technological portfolios for climate-change policy with “multiple” mitigation options and “international” spillover effects

Each economy n produces a single final good. Individual utility depends on consumption of the final good and on the quality of the environment (e.g., global mean temperature). The environmental quality can be augmented only by reductions in carbon emissions via the following four technological options: energy-efficiency improvement, substituting into less carbon-emitting energy sources, or supplying new carbon-free ‘backstop’ or nuclear alternatives.

Economic activity is described by a production function and uses of output. Output at time t , $Y(n, t)$, depends on the inputs of labor $L(n, t)$, general physical capital $K_C(n, t)$, and energy-efficiency knowledge capital $K_\chi(n, t)$:

$$\begin{aligned} Y(n, t) &= \Omega(D(n, t)) K_C(n, t)^\gamma (A(n, t) L(n, t))^{1-\gamma} K_\chi(n, t)^\beta \\ &= C(n, t) + I(n, t) + I_\chi(n, t) + I_\omega(n, t) + I_\nu(n, t) + I_\varepsilon(n, t) \end{aligned} \quad (C1)$$

where $A(n, t)$, labor productivity, is assumed to increase with decreasing rate over time following $A(n, t) = [1 + g_A(n, t)]A(n, t - 1)$. Labor is determined by exogenous population growth and capital stock is accumulated in the usual fashion. Output (net of climate damage $D(n, t)$) is available for private consumption $C(n, t)$, private investment $I(n, t)$, and the three forms of carbon mitigation efforts including investments in energy efficiency

improvements $I_\chi(n, t)$, in substitution technology $I_\omega(n, t)$, in backstop technology $I_\nu(n, t)$, or in nuclear technology $I_\varepsilon(n, t)$. Similar to a physical general capital, these energy-specific knowledge/experience stocks are generated by the accumulation of previous investment and efforts:

$$K_i(n, t) = I_i(n, t) + (1 - \delta_i)K_i(n, t - 1), \quad i = c, \chi, \omega, \nu, \varepsilon. \quad (C2)$$

In the model, emissions from burning fossil fuels are identified as carbon, and they can be reduced either indirectly by the rate of energy-efficiency improvements, $\chi(n, t)$, or directly by controlling the carbon emissions with the rate of substitution effort, $\omega(n, t)$, the rate of backstop supply $\nu(n, t)$, and the rate of nuclear supply $\varepsilon(n, t)$. The carbon emissions are thus written as

$$E(n, t) = \sigma(n, t)[1 - \chi(I_\chi(n, t), K_\chi(n, t))][1 - \omega(n, t) - \nu(n, t) - \varepsilon(n, t)]Y(n, t), \quad (C3)$$

where $\sigma(n, t)$, the business-as-usual carbon emissions intensity of production, is regarded as declining exogenously with decreasing rate over time due to “autonomous energy-efficiency improvement” (AEEI) following $\sigma(n, t) = \sigma(n, t - 1) / [1 + g_\sigma(n, t)]$.

The rate of technological change pertaining to energy-efficiency improvement $\chi(n, t)$ is assumed to follow the typical innovation possibility frontier

$$\chi(n, t) = e_1(n)I_\chi(n, t)^{e_2(n)}K_\chi(n, t)^{e_3(n)}\left[\sum_n K_\chi(n, t)\right]^{e_4(n)}. \quad (C4)$$

On the other hand, the cost of each of the “direct” carbon mitigation options, $\omega(n, t)$, $\nu(n, t)$ and $\varepsilon(n, t)$ in terms of output is assumed to be

$$I_i(n, t) = c_{0i}(n)[K_i(n, t)]^{-\alpha_i(n)}\left[\sum_n K_i(n, t)\right]^{-\phi(n)}[i(n, t)]^{c_{ii}(n)}Y(n, t), \quad (C5)$$

where $i(n,t) = \omega(n,t)$, $v(n,t)$, $\varepsilon(n,t)$, respectively and where c_{0i} is a normalization parameter and $\alpha_i(n)$ is the learning elasticity index (Messner 1997, Anderson, 1999). Note here that the technological progress is also represented as a decreasing function of cumulative installed capacity and pertains to investment costs for each of the technologies.

At each point in time, given the knowledge stocks, the optimal technological portfolio for multiple mitigation efforts is determined where marginal costs of technologies are all equalized to each other and to marginal benefit of mitigation (Figure C1).

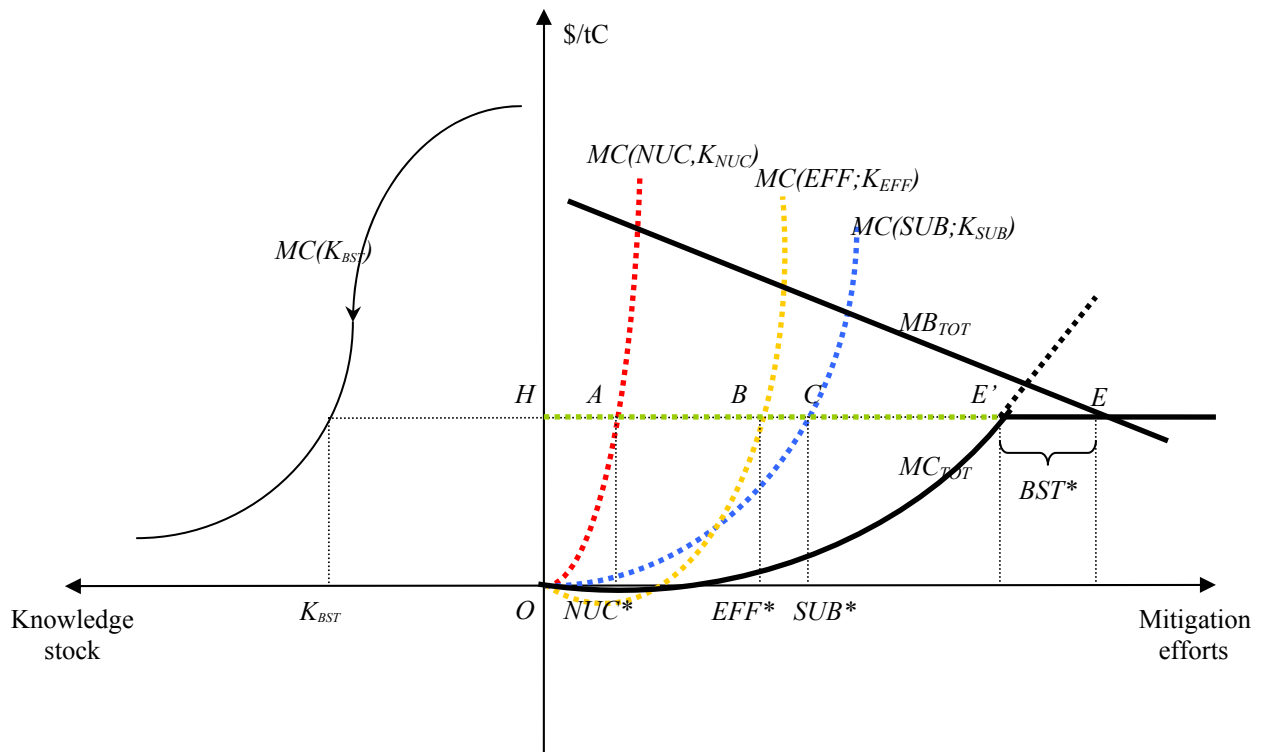


Figure C1. A conceptual illustration of knowledge accumulations, marginal costs and their technological portfolios

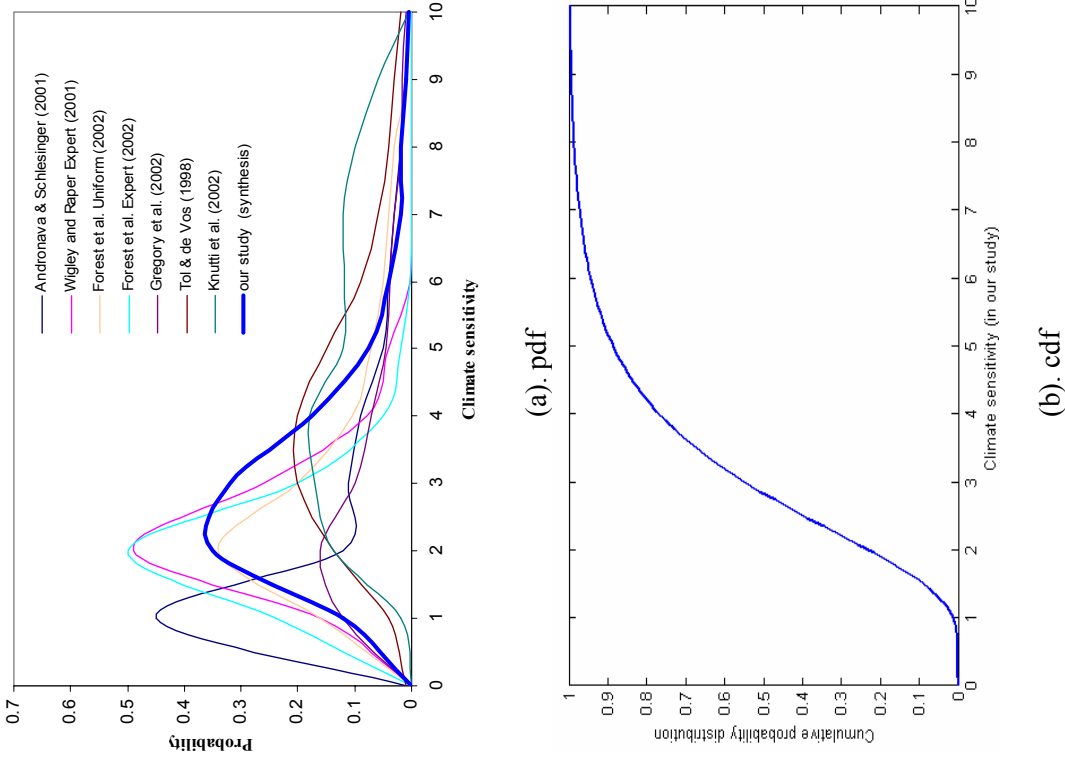


Fig. 1. Deriving probability distribution of uncertain climate sensitivity for our study. Shown in Fig. 1(a) are the recent probability distributions (pdf) estimates for climate sensitivity from a number of recent studies [based on Dessai et al. (2003)] and our averaged synthesis approximated by log-normal probability distribution. Most of these recent studies produce distributions wider than the IPCC range (1.5 – 4.5°C).

Fig. 1(b) displays the corresponding cumulative probability distribution (cdf) adopted for our present study, which yields 10th, 50th, and 90th percentile for climate sensitivities of 1.5°C, 2.8°C, and 5.2°C, respectively.

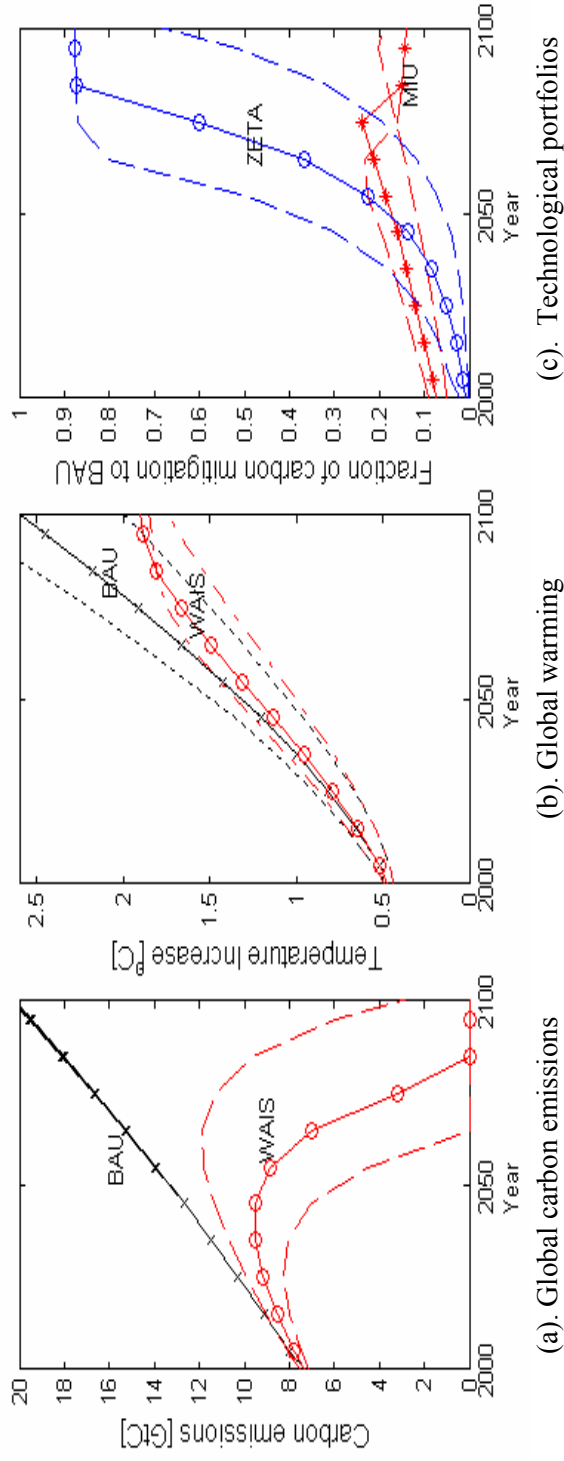


Fig. 2. Band estimation for carbon emissions, global warming and technology choice over time: BAU vs. WAIS. Shown are the probabilistic ranges for (a) global carbon emissions, (b) global mean temperature increase, and (c) carbon mitigation technology portfolio over time. Lower and upper dashed lines in each panel refer to 1st quartile and 3rd quartile values in the distribution, respectively. In Fig. 2(a) and (b), BAU represents “no policy” and WAIS is “2.5 °C temperature stabilization policy.” In Fig. 2(c), MIU refers to “conventional mitigation technology” and ZETA refers to “new, carbon-free technology” (e.g., renewables and backstops approximately including solar/wind powers, carbon sequestration, hydrogen, biomass, etc.) under the WAIS case.

Fig. 3. Distribution of the economic effects of WAIS policy under alternative scenarios. “Central” scenario assumes the case with reference labor productivity growth (1.4%/yr) and reference AEEI growth (1.3%/yr), based on the historical trends. (i). “HH” case is with higher labor productivity growth (=2.5%/yr) and higher AEEI growth (=2.2%/yr). (ii) “HL” case is with higher labor productivity growth (=2.5%/yr) and lower AEEI growth (=0.5%/yr). (iii) “LH” case is with lower labor productivity growth (=0.8%/yr) and higher AEEI growth (=2.2%/yr). (iv) “LL” case is with lower labor productivity growth (=0.8%/yr) and lower AEEI growth (=0.5%/yr). In Fig. 3(a), the “WAIS wedge” is defined as the gap between carbon emissions of BAU and WAIS in a specific year.

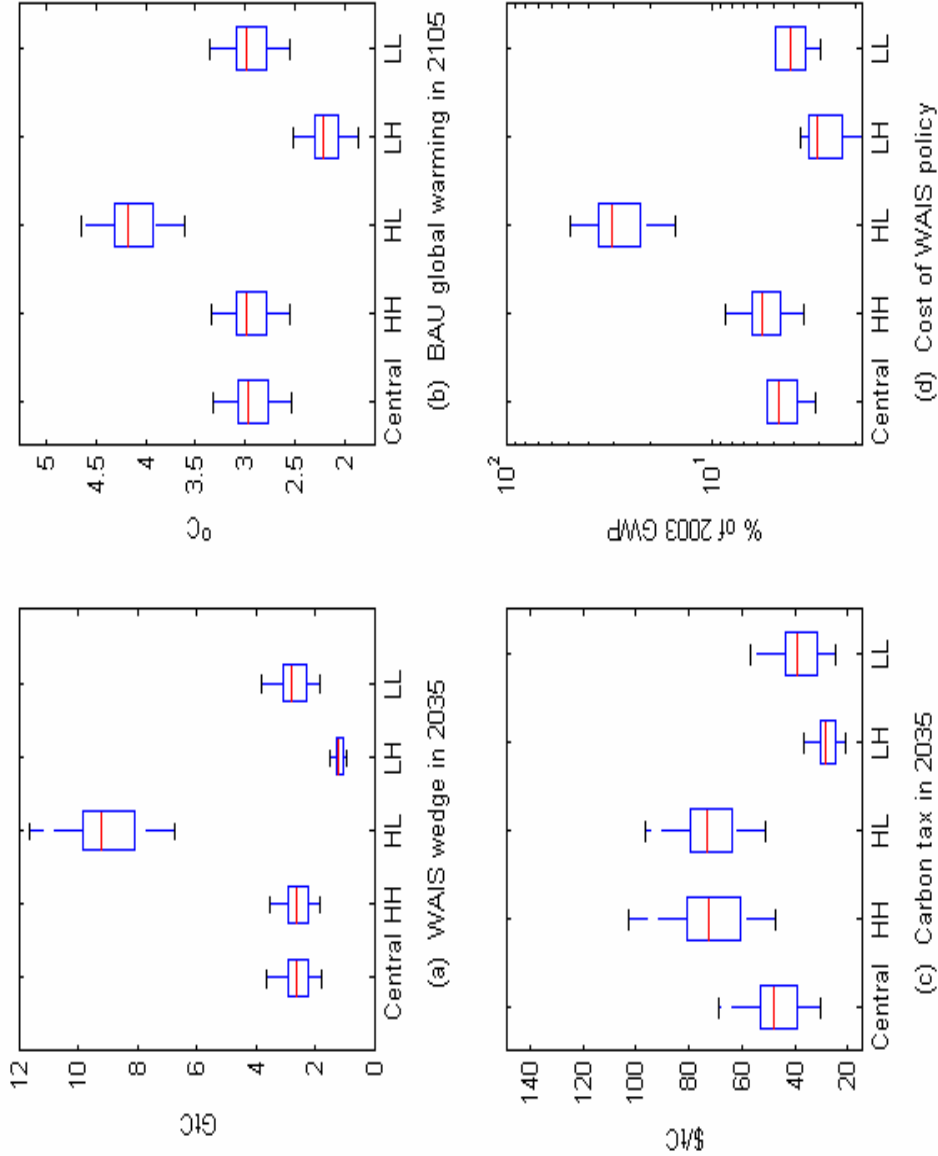


Fig. 4. Distribution of “regrets” as a function of procrastination. The “regrets,” as a social cost of procrastination, is approximated by the net-present value of the future consumption losses of optimal policies “with each specific procrastination constraint” (*i.e.*, no carbon control for a specific number of years), relative to “without procrastination activities” (*i.e.*, ‘act now’ policy for the WAIS). It is shown that the possibility and risk of probabilistic “regrets” can increase substantially with the years of procrastination. Note that the scale for x-axis is logarithmic.

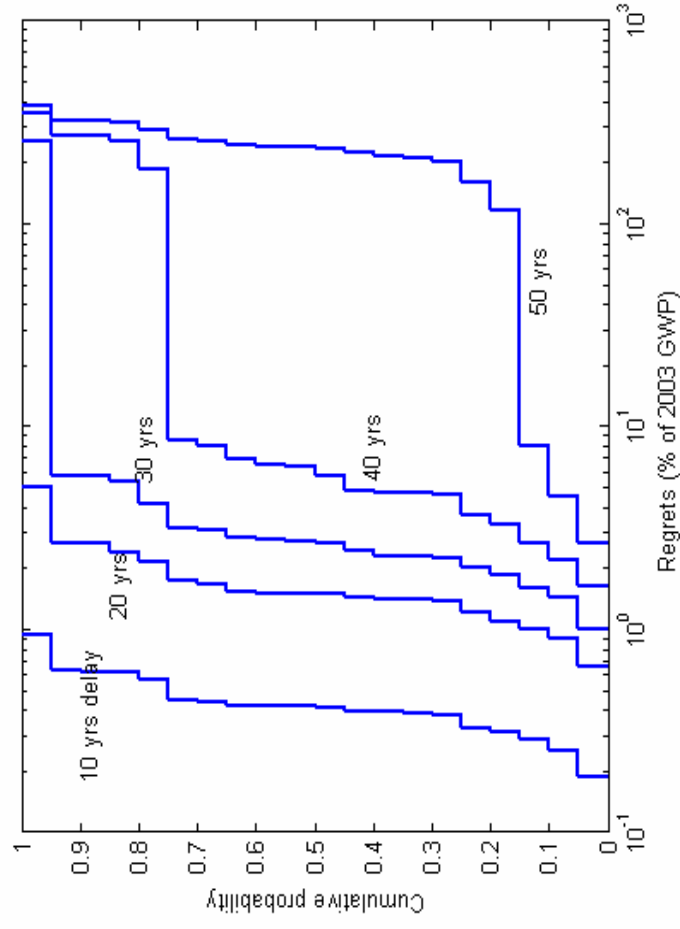


Fig. 5. The modeled relationship between the procrastination period and the probability of exceeding “critical level of regrets (CR)”. The solid lines indicate the probability of having outcomes above the stated threshold of critical regrets for the policy-maker for any given level of years of procrastination. For example, at a relatively high value of CR = 10% of 2003 GWP, the Prob[“regrets” > CR] increases from near 0% with 30 yrs of procrastination to almost 75% with 60 yrs of procrastination. It is also shown that for most of a plausible range of CR values, the possible risks and economic consequences of procrastination (in terms of economic burden) would go abruptly severe just within 30 - 60 yrs (i.e., the chance of regrets exceeding a modest range of economic burden thresholds increases rapidly from near 10% to almost 90% regardless of the stated thresholds).

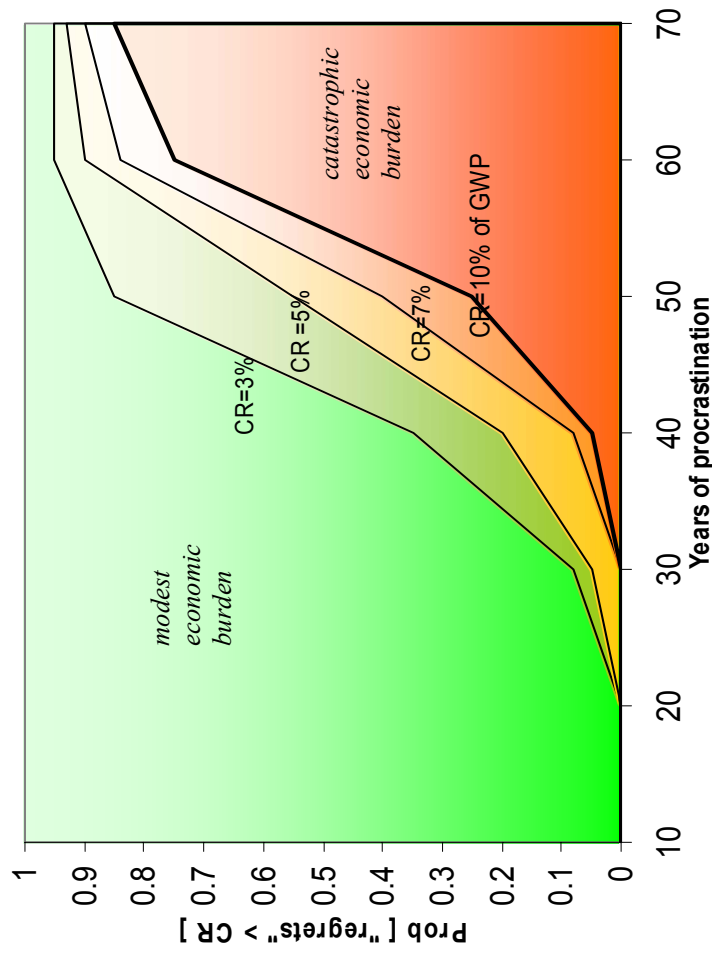


Fig. 6. Distribution of probabilistic “regrets” under alternative economic and natural circumstances. Shown are the distribution of possible regrets for the WAIS case, depending on major assumptions about future economic activity (labor productivity growth), future technological improvement in energy technologies (AEEI growth), and tighter climate threshold ($\approx 2^\circ\text{C}$ limit). As we would expect, the possible regrets rises with the higher labor productivity growth and falls with optimistic AEEI growth in a significant manner. In addition to these key uncertain economic parameters, in particular the probabilistic range of regrets increases greatly with a tighter climate threshold.

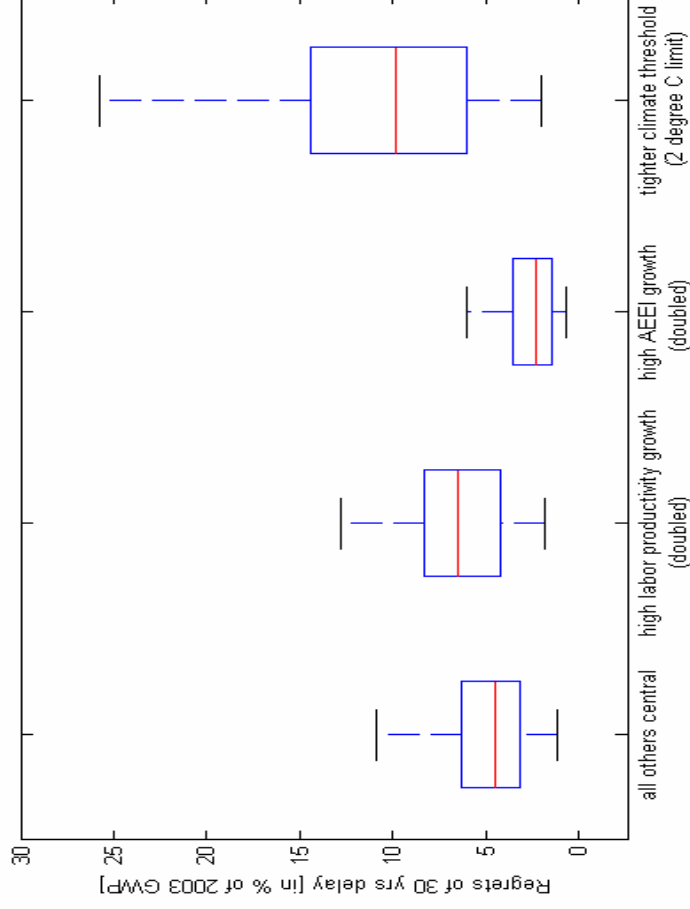


Fig. 7. Probability of exceeding critical level of “regrets” as a function of major uncertain economic and natural assumptions. With 30 yrs of delay in WAIS policy, Fig. 7(a) and (b) display the probability of having dangerous regrets above 5% of 2003 GWP and above 10% of 2003 GWP, respectively. As indicated, optimistic energy technology reduces significantly the possibility of the outcome’s exceeding the stated burden threshold, compared to the central case. On the contrary, it is shown that labor productivity enhancement (a proxy for general economic productivity growth without AEEI improvement) and, more seriously, tighter climate threshold (2 °C limit) call for more risky treatments of procrastination policy and regrets implications.

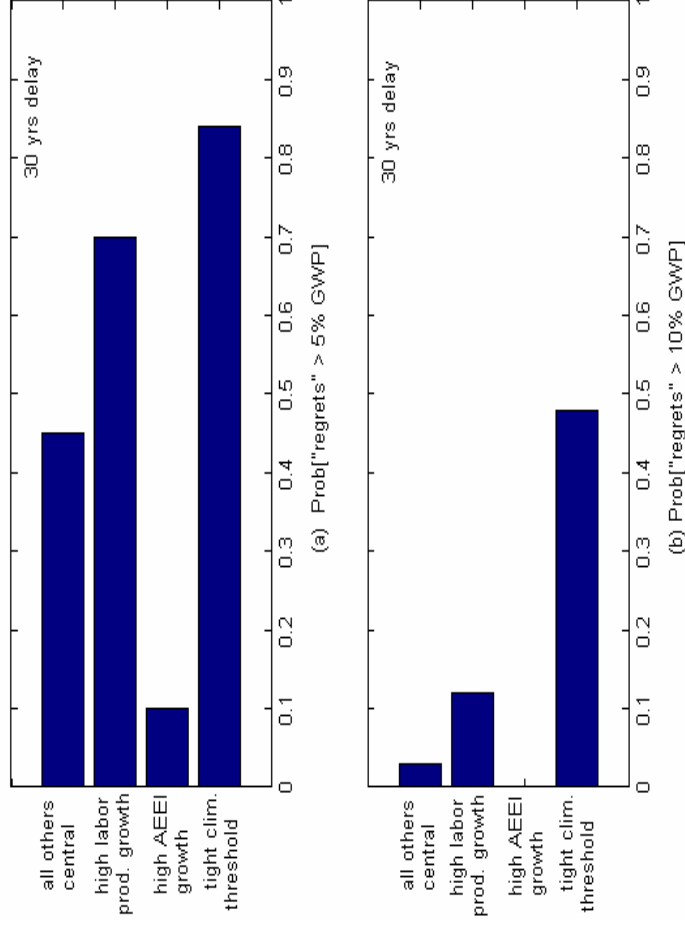
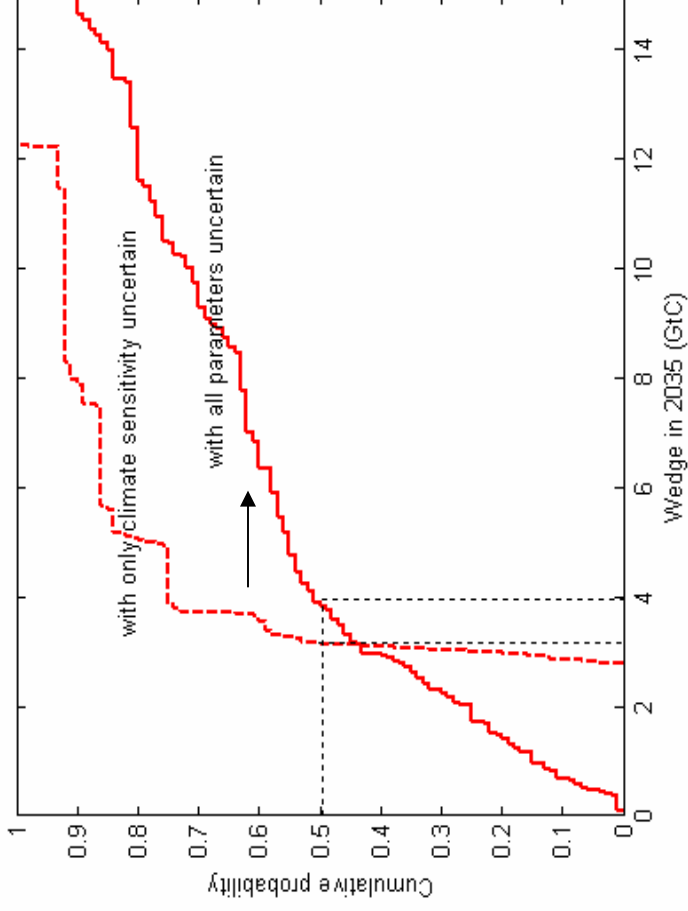


Fig. 8. Distribution of the WAIS wedge in 2035 under alternative scope of parameter uncertainty.

The “wedge” here is defined as the gap between carbon emissions of BAU and WAIS in a specific year. This figure compares the required wedges in 2035 “with only climate sensitivity uncertain” (dashed line) to “with all parameters uncertain” (solid line). In most cases, the estimates of all other uncertain economic parameters (except for our climate sensitivity) are drawn from the relevant literature (Nordhaus, 1994; Nordhaus and Popp, 1997; Pizer, 1999). As implied in the literature, ignoring more uncertainty tends to lower the stringency of optimal policy. It is shown that, relative to the natural parameter uncertainty (i.e., climate sensitivity), considering more uncertainties surrounding other economic parameters into our model increases the median (50th percentile) wedge value by about 30%.



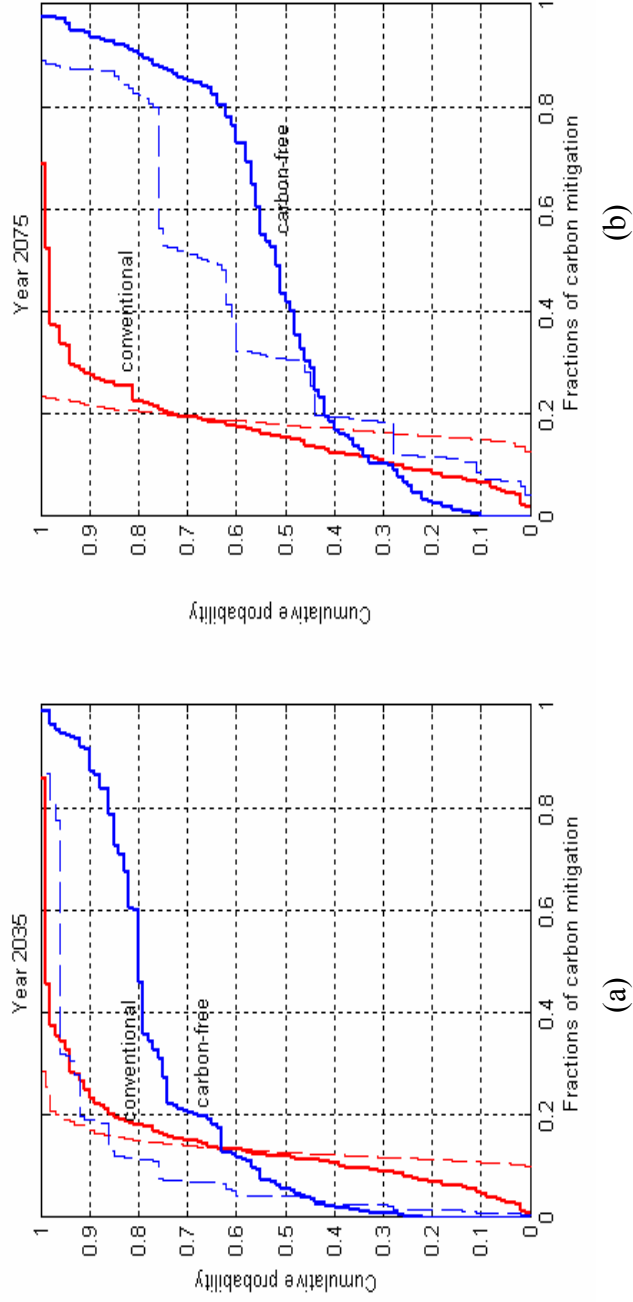
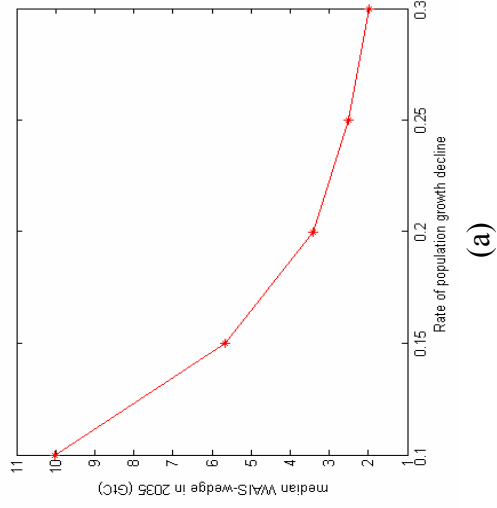
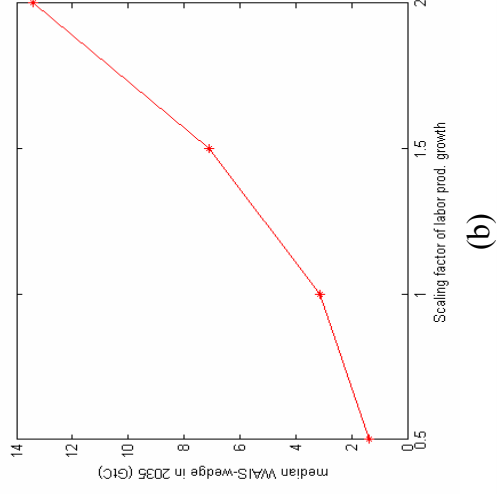


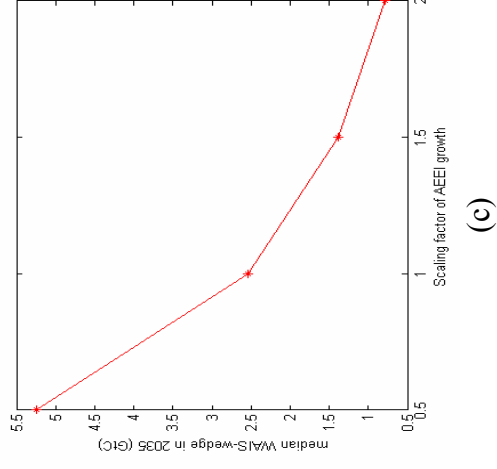
Fig. 9. Distribution of carbon mitigation technologies: Conventional vs. Carbon-free technology. Shown are the distributions of efficient choice of carbon mitigation technologies under the WAIS (a) in 2035 and (b) in 2075, respectively. For each technology, the dashed line refers to the outcomes from “with only climate sensitivity uncertain” case, and the solid line from “with all parameters uncertain” case.



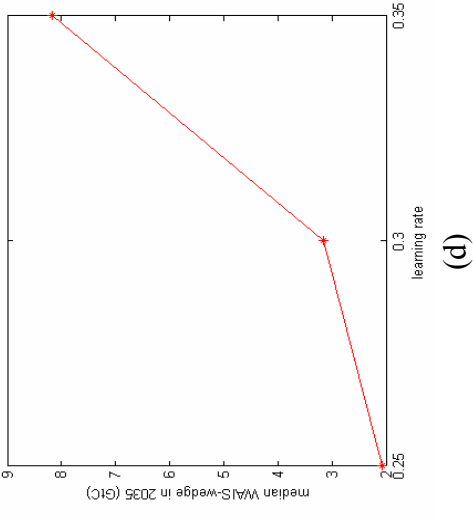
(a)



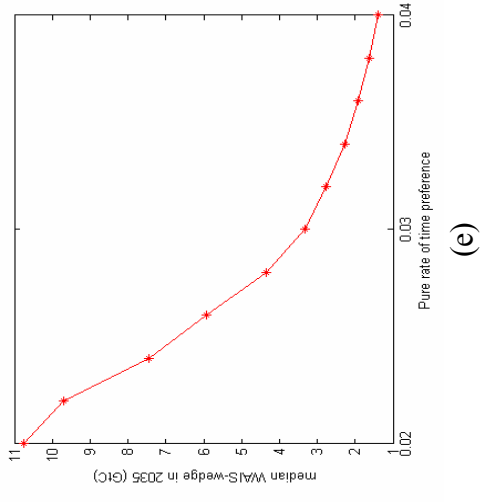
(b)



(c)



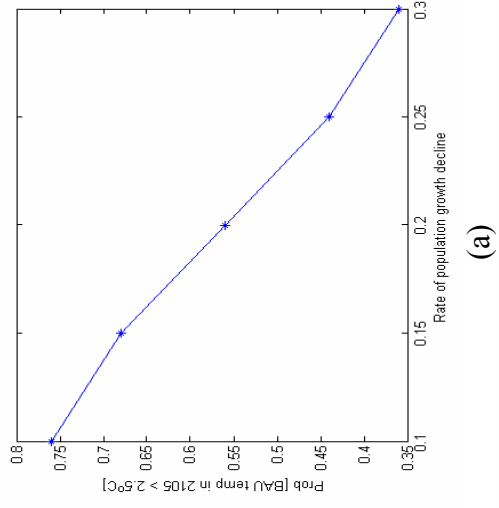
(d)



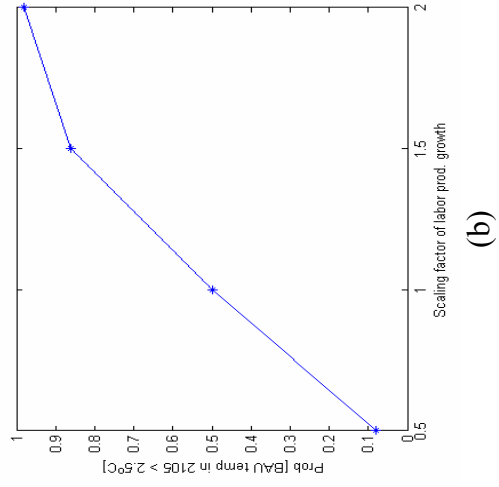
(e)

Fig. 10. Sensitivity of the median WAIS “wedge” value in 2035 to various uncertain model parameters:

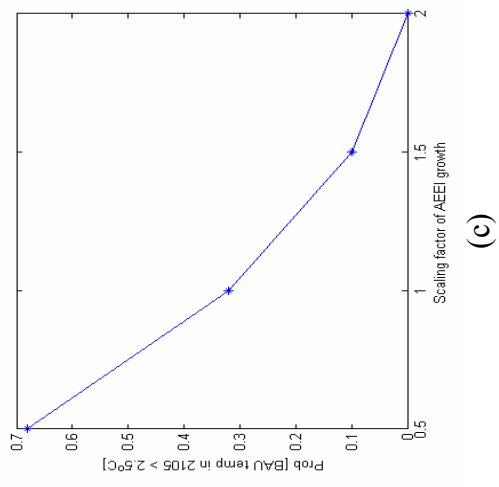
- (a) rate of population growth decline,
- (b) scaling factor of labor prod. growth,
- (c) scaling factor of AEEI growth,
- (d) technological learning rate, and
- (e) pure rate of time preference.



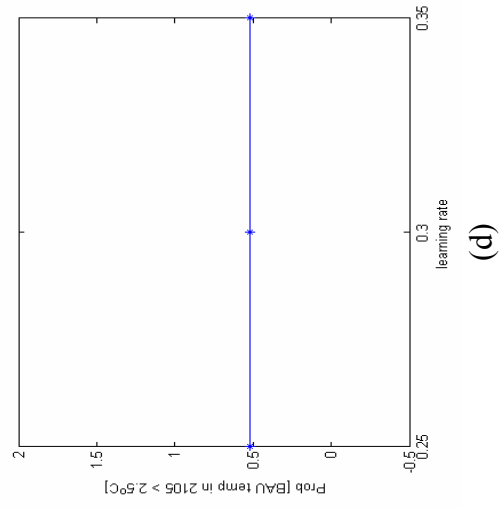
(a)



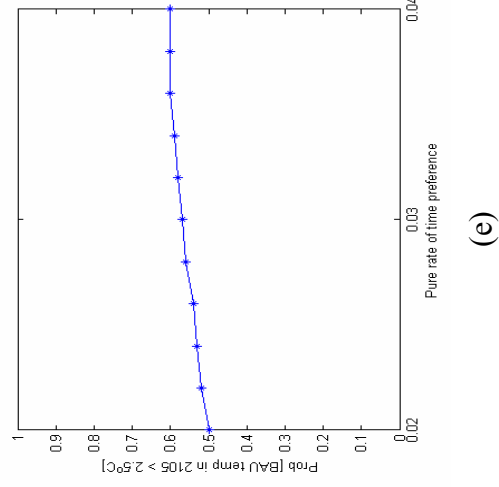
(b)



(c)



(d)



(e)

Fig. 11. Sensitivity of Prob [BAU global warming in 2105 > 2.5°C] to various uncertain model parameters:
 (a) rate of population growth decline,
 (b) scaling factor of labor prod. growth,
 (c) scaling factor of AEEI growth,
 (d) technological learning rate, and
 (e) pure rate of time preference.

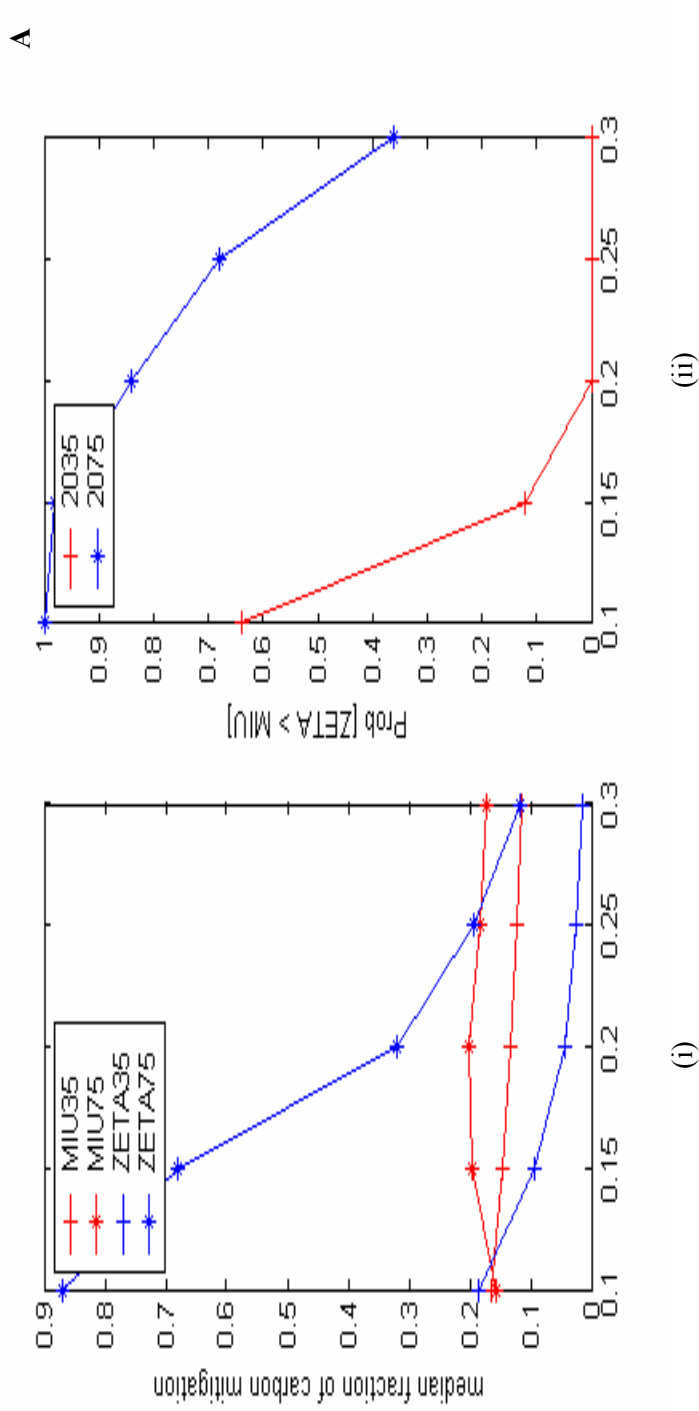


Fig. 12a. Effect of the uncertain rate of population growth decline on technological portfolios. MIU refers to “conventional technology” and ZETA refers to “carbon-free technology” in 2035 and in 2075. Fig.12a-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the uncertain rate of future population growth decline. Fig.12a-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *decreases* with the rate of population growth decline.

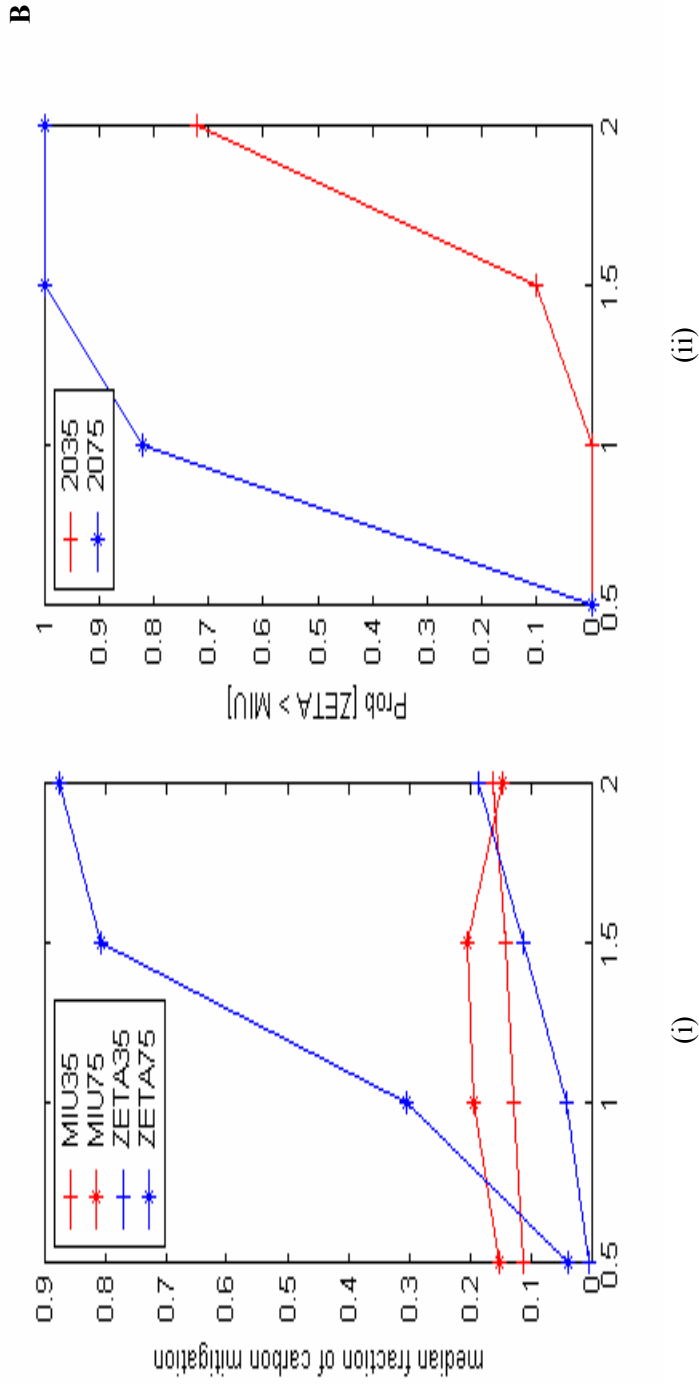
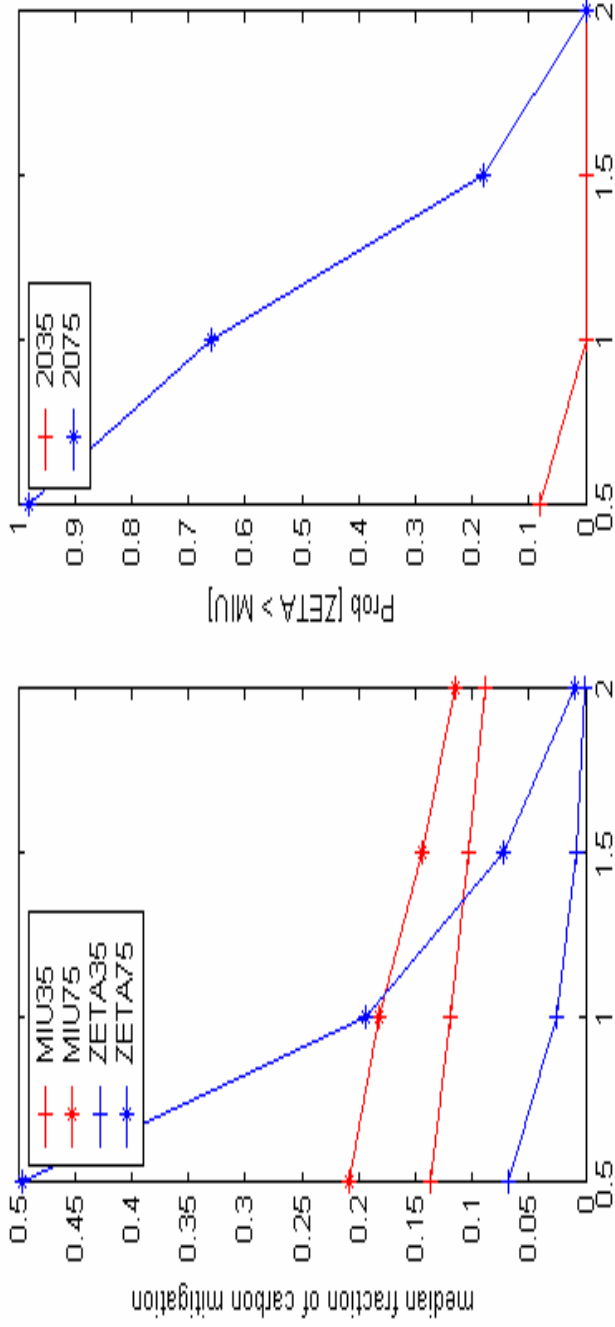


Fig. 12b. Effects of uncertain labor productivity growth on technological portfolios. MIU refers to “conventional technology” and ZETA refers to “carbon-free technology” in 2035 and in 2075. Fig.12b-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the degree of uncertain future labor productivity growth. Fig.12b-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *increases* with the labor productivity growth.

C



(i)

(ii)

Fig. 12c. Effects of uncertain AEEI growth on technological portfolios. MIU refers to “conventional technology” and ZETA refers to “carbon-free technology” in 2035 and in 2075. Fig.12c-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the degree of uncertain future AEEI growth. Fig.12c-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *decreases* with AEEI growth.

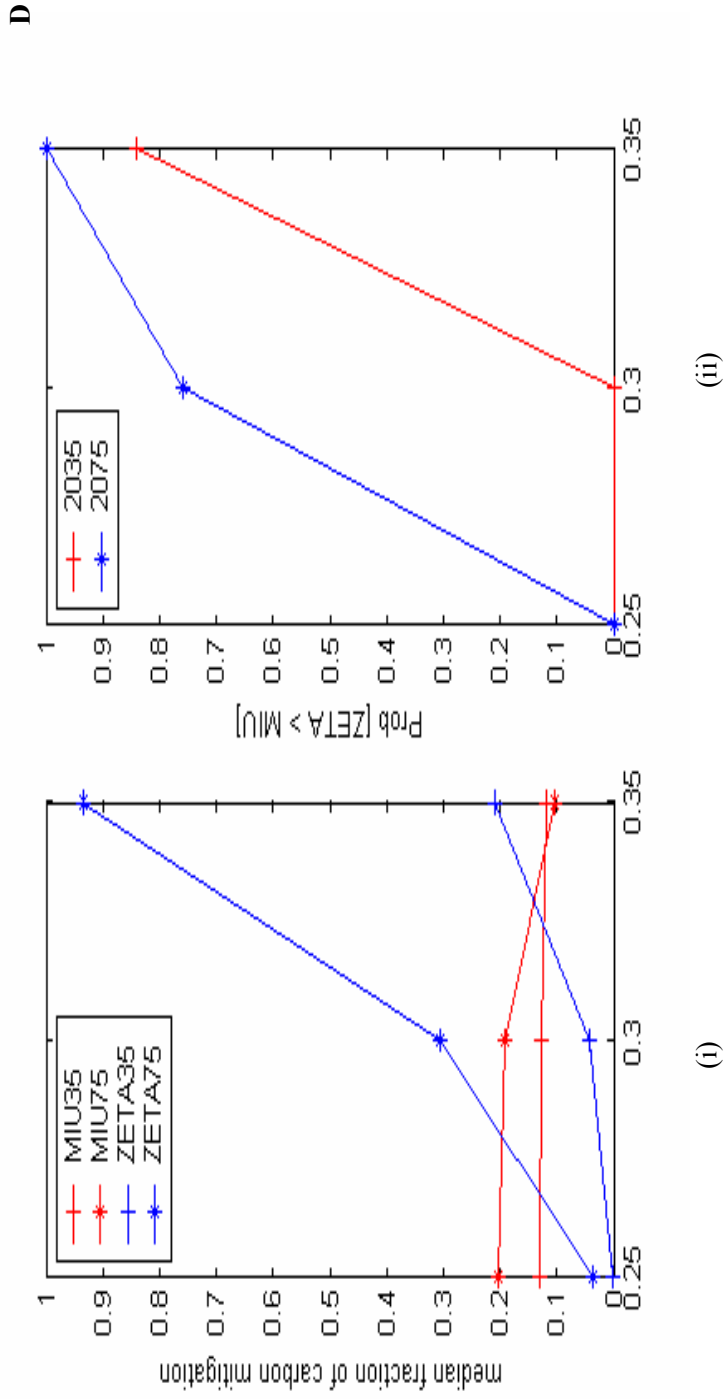
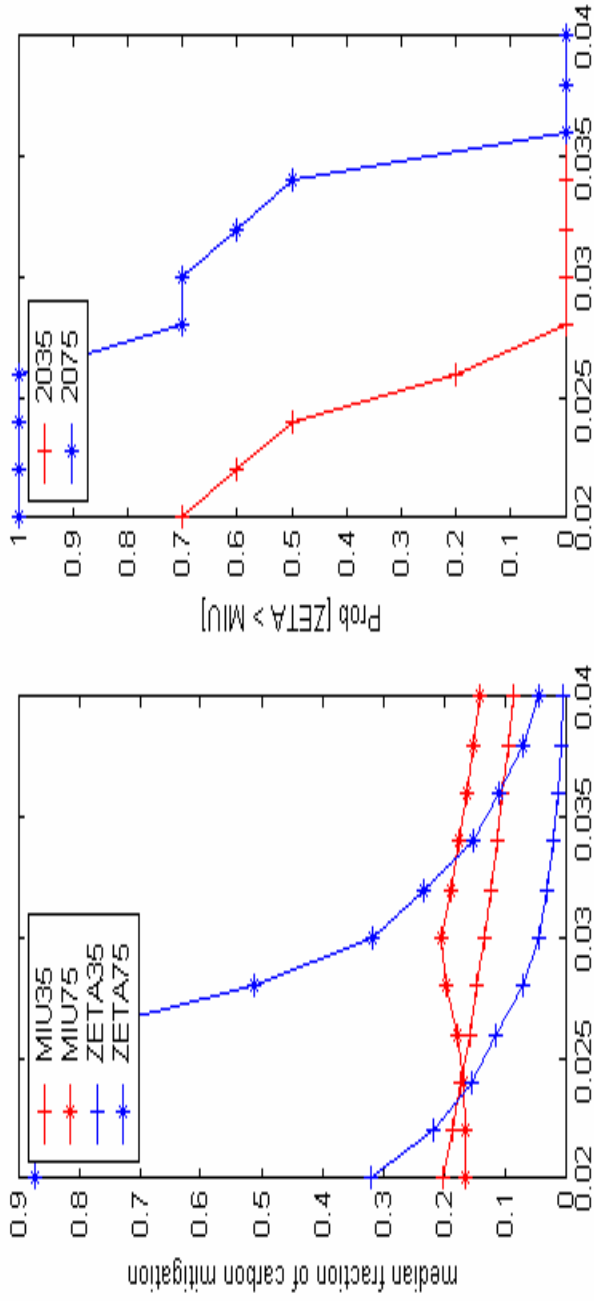


Fig. 12d. Effects of learning rate on technological portfolios. MIU refers to “conventional technology” and ZETA refers to “carbon-free technology” in 2035 and in 2075. Fig. 12d-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the uncertain technological learning rate for ZETA. Fig. 12d-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *increases* with the technological learning rate for ZETA.

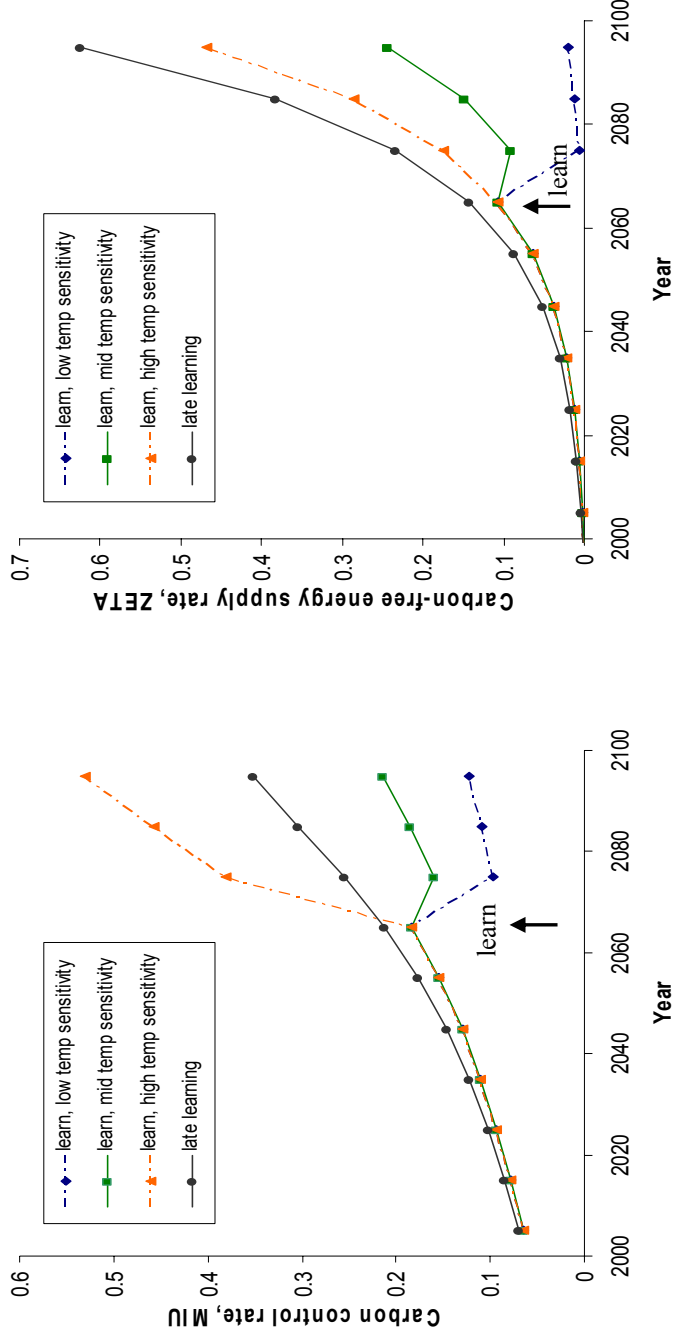
E



(i)

(ii)

Fig. 12e. Effects of pure rate of time preference on technological portfolios. MIU refers to “conventional technology” and ZETA refers to “carbon-free technology” in 2035 and in 2075. Fig. 12e-(i) displays how the optimal median technological portfolio values for MIU and ZETA respond to the uncertain pure rate of time preference. Fig. 12e-(ii) shows that the probability of ZETA’s exceeding MIU (in the role of carbon mitigation) *decreases* with the pure rate of time preference.



(a). Conventional technology

(b). Carbon-free technology

Fig. 13. Learning, hedging and the value of early information. Figure 13(a) and (b) show the effects of learning about uncertain climate sensitivity in 2065 (compared to late learning) on optimal mitigation policies, MIU and ZETA, respectively. We assume equal probability of three true state of the world about climate sensitivity. Before learning in 2065, policies cannot be state-contingent, and thus are equal in all state of the world. Uncertainty raises optimal level for each of the technology policies significantly.

Fig. 14. Range of values of scientific knowledge about the climate sensitivity for different years of resolution and their sensitivities to assumptions on technological progress and climate limit.

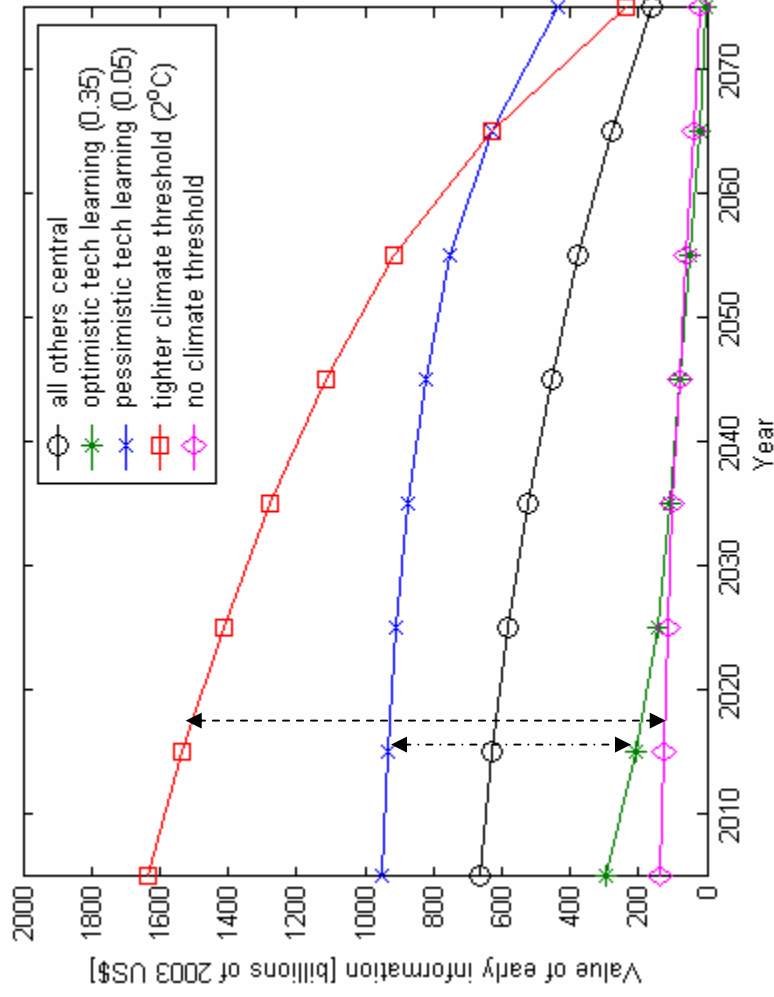


Fig. 14 estimates the value of scientific knowledge about the climate sensitivity variables depending upon the year in which uncertainties are revealed. Here we compare the present value of increased utility of consumptions for each case relative to the case where perfect information is attained in 2085 across alternative assumptions about the technological learning rate and the climate threshold. The results imply that the value of early information can be highly dependent upon how fast the uncertainty will narrow over time and that it can be extremely large with pessimistic technological progress and tighter environmental goals, and *vice versa*.