ABSTRACT

Title of Dissertation: ENERGY TECHNOLOGY DEVELOPMENT
                              AND CLIMATE CHANGE MITIGATION

                              Haewon C. McJeon, Doctor of Philosophy, 2012

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This dissertation examines the role that technology plays in climate change mitigation. It contains three essays each focusing on different aspects of the process in which advancements in low-carbon energy technologies impact the cost of carbon dioxide (CO_2) abatement.

The first essay develops the analytical foundation for understanding how heterogeneous low-carbon energy technologies induce differential impacts on the abatement cost. The analysis derives sets of conditions under which different types of advanced technologies can be evaluated for their respective strengths in reducing abatement costs at different levels of abatement. It emphasizes the weakness of a single point estimation of the impact of a technology and the importance of understanding the pattern of abatement cost reductions throughout the potential levels of abatement.

The second essay focuses on the interactions of the energy technologies in the market. The analysis uses a combinatorial approach in which 768 scenarios are created for all combinations of considered technology groups. Using the dataset, the analysis shows how the reduction in the abatement cost may change significantly depending on

the existence of other advanced technologies. The essay shows that many of the fundamental insights from traditional representative scenario analyses are in line with the findings from this comprehensive combinatorial analysis. However, it also provides more clarity regarding insights not easily demonstrated through representative scenario analyses. The analysis emphasizes how understanding the interactions between these technologies and their impacts on the cost of abatement can help better inform energy policy decisions.

The third essay focuses on the impact technological change has on the cost of abatement, but with special attention paid to the issue of delayed technology development. By combining the probability of advanced technology success estimates from expert elicitations with the abatement cost data estimated with an integrated assessment model, a stochastic dynamic programming model is developed. A multi-period extension of the model allows intertemporal dynamic optimization where the policy-maker can select the technologies to be invested in immediately and the technologies to be invested in later. The analysis emphasizes the benefit of having a wait-and-see option that lets the policy-maker further optimize upon the observation of successes and failures of prior investments.

The three essays collectively serve to demonstrate the importance of clearly understanding the differences among low-carbon technologies. They also provide methodological foundations upon which such technologies can be assessed and compared. Combining these methods with an enhanced understanding of the technologies will contribute to the body of research aimed at minimizing the cost of mitigating climate change.

ENERGY TECHNOLOGY DEVELOPMENT
AND CLIMATE CHANGE MITIGATION

By

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Dissertation submitted to the Faculty of the Graduate School of the
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Professor Matthias Ruth, Chair
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To 愛隣

Acknowledgements

So it really did take a village.

It all started with a meeting one spring day with the two of my future committee members. My then Master's advisor, Matthias Ruth, called the meeting thinking that I would be a good fit as a research assistant for a new project at the Joint Global Change Research Institute (JGCRI). My participation in this long-term collaboration project meant that my fate was essentially sealed: I would continue my studies at the Maryland School of Public Policy (MSPP) as a PhD student. For Matthias's excellent guidance throughout my six years as a graduate student following that meeting, and for serving as the chair of my dissertation committee, I cannot be more grateful.

I met the other future committee member, Leon Clarke of JGCRI, for the first time that day. I am indebted to Leon for the dual role he played throughout the years, as both a very considerate boss and as an inspiring mentor. Leon also introduced me to the GCAM modeling team of JGCRI. GCAM is the research platform used throughout this dissertation, and the dissertation would not have been possible without the talented group of people who have put such great effort into building this world-class integrated assessment model. I am very proud to call myself a member of this team.

I'd like to extend a special thank you to the founding father of GCAM, Jae Edmonds. Without his vision at the dawn of climate and energy modeling, the integrated assessment modeling community would not be where it is today. I'm honored to have Jae on my committee.

As an Associate Director of JGCRI, Nate Hultman serves as a bridge between the University and the research institute. I am grateful for both his practical help in this

regard, and for his thoughtful policy insights. With his passion for making the world a better place one energy research project at a time, he is a clear role model for young, aspiring scholars,

This dissertation would not have the analytical structure it has now if it wasn't for that one fall semester sitting in Lars Olson's class. I had hit a wall developing the structure for the first essay, but the course taught me how to think clearly through an analytical model. And I am honored to have him on my committee as the Dean's Representative.

The first research I did with GCAM (then called MiniCAM) was simply to generate a number of abatement cost curves. This analysis eventually evolved into my first essay. I am indebted to Erin Baker and Jeffrey Keisler for letting me collaborate with them on what turned out to be a very productive project. All the technology definitions and expert elicitations data I used in the first and the third essays are the original works of Baker and Keisler. My contribution to the partnership was to take the technology definitions and process them through GCAM, generate the model results, and document the procedures. The first essay is essentially a collection of my own contributions to the journal articles we've published together, with the addition of my own literature review and analytical framework.

The second essay started as collaboration between JGCRI and a group at RAND led by Robert Lempert. An extended version of this essay is published as McJeon et al. (2011) which is my first first-authored journal article. My role in this project was to conduct the parallel processing of technology permutations, to visualize and analyze the results, and to write the corresponding sections of the article. While the essay in this

And it goes without saying that I alone am responsible for the views expressed in this dissertation as well as for any errors that may remain.

Finally, to my family. My parents raised me in a way that prepared me well for a career in this field. They taught me the importance of having a warm heart to care about the problems in the world, as well as a cool head to find the most efficient way to solve these problems. I only hope that my wife and I will be able to replicate their perfectly balanced approach with our own children.

Economists are trained to be rational, always rigorously reasoning through the issues before them. But all too often, we fall victim to our own narrow definitions of rationality, and stray farther than we would like from what is truly reasonable. If my essays have narrowly avoided such a mistake, all the credit goes to my wife, Erin. She spent so many weekends reading through one draft after another, and provided me with a great deal of thoughtful and sensible feedback. Throughout my graduate school years, she has been my external voice of reason, and I'm grateful that it will stay that way for the rest of our lives.

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Chapter 1: Introduction

Fossil fuels constitute over 80% of current world primary energy consumption (IEA, 2010). The problem is that combusting fossil fuels for energy production inevitably results in emissions of carbon dioxide (CO_2), the largest contributor of anthropogenic global warming among known greenhouse gases in the atmosphere. Globally reducing greenhouse gas (GHG) emissions to mitigate climate change would require either a substantial conservation of energy or a substantial shift in energy sources. However, any major shift away from fossil fuels to low-carbon energy sources—such as solar, wind, biomass, nuclear, etc.—would require overcoming currently existing obstacles, including high cost, insufficient capacity, and, in the cases of solar or wind, intermittency.

Technological changes through innovations in alternative energy technologies may provide solutions to overcome—partially or completely—these obstacles. For instance, new energy production methods may bring down costs; more efficient extraction of energy may allow large scale deployments; and low-cost storage technology may relax intermittency constraints. An obvious benefit of such technological change is being able to switch to these alternatives at a cost low enough and at a scale large enough to abate CO_2 emissions substantially.[1]

In order to make the most efficient use of limited public resources, public research and development (R&D) investment in technological change should be targeted to maximize the net social benefit per dollar invested. Figure 1.1 shows how the R&D investment for technological change affects climate stabilization policies. Public R&D

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[1] On the other hand, there may be unintended consequences to technological change. Advancements in alternative energy technologies may induce increased energy consumption, which in turn would partially offset the mitigation effect. See "rebound effect" in Section 2.3. Secondary effects of reduced energy costs also include accelerated economic growth, which in turn may further increase overall energy consumption.

policy for energy technology is a classic example of decision-making under uncertainty. R&D investments in energy technologies stochastically induce technological change in the forms of cost reductions, capacity increases, emission reductions, and so on. The relationship between R&D and technological change is not deterministic. Some technologies may succeed, while others fail to deliver the change. The probability of successful technological change is dependent upon the amount of investment.

These technological changes, in turn, affect the future shares of the technologies in the energy market. The deployment of successfully developed advanced technology increases, while other competing technologies lose some of their market shares. As a result of the market adjustments, the magnitude of the reduction in the cost of GHG abatement is determined. In the final stage, the resulting cost of abatement is combined with the expected damages[2] from climate change to jointly inform the policy decision on the optimal level of equilibrium emissions.
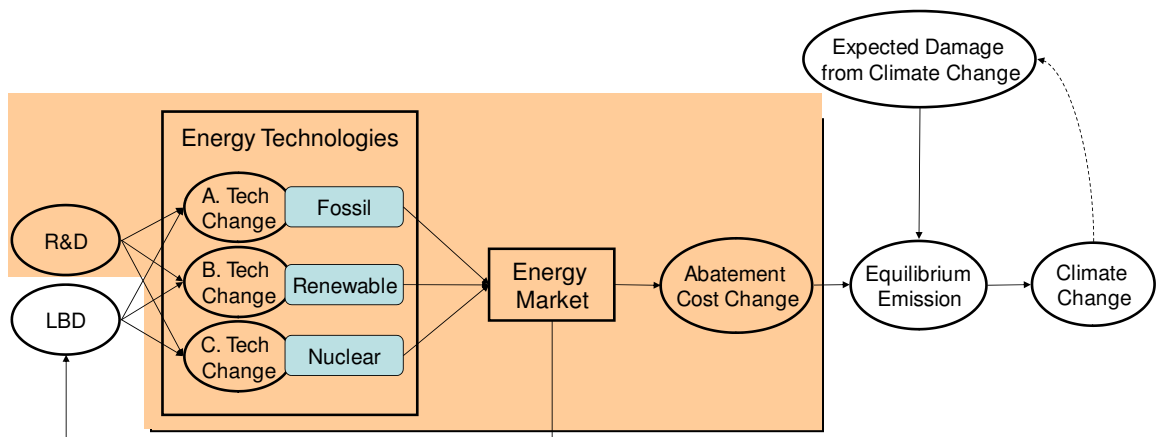
Figure 1.1: Schematics of the impact of technological change on climate stabilization policy

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[2] It should be noted that with our current knowledge of climate change, the expected damage is also highly uncertain and the estimates are in severe disagreements with one another. For monetization of future damages from climate change, see for example, Nordhaus (1994); Tol (2002a, 2002b); and Stern (2006).

The focus of this dissertation is the shaded subset of this process: how R&D stochastically affects technological changes, how technological changes affect the mix of energy technologies in the market, and how the interactions of the technologies in the market affect the cost of CO_2 abatement. The processes outside the shaded area are beyond the scope of this dissertation: how the equilibrium mix of energy technologies in the market dynamically induces learning-by-doing and how estimated climate damage projections, jointly with the cost of abatement, determine the equilibrium emission level.

This dissertation contains three essays, each focusing on different aspects of the dynamics between technological change and climate change mitigation. The first essay presented in Chapter 2 focuses on how advancements in an energy technology impact the cost of CO_2 abatement. Specifically, the essay develops the analytical foundation for understanding how heterogeneous low-carbon energy technologies induce differential impacts on the abatement cost. The analysis derives sets of conditions under which different types of advanced technologies can be evaluated for their respective strengths in reducing abatement costs at different levels of abatement. It emphasizes the weakness of a single point estimation of the impact of a technology and the importance of understanding the pattern of abatement cost reductions throughout the potential levels of abatement.

The second essay presented in Chapter 3 focuses on the interactions of the energy technologies in the market. The analysis uses a combinatorial approach in which 768 scenarios are created for all combinations of considered technology groups. Using the dataset, the analysis shows how the reduction in the abatement cost may change significantly depending on the existence of other advanced technologies. The essay

shows that many of the fundamental insights from traditional representative scenario analyses are in line with the findings from this comprehensive combinatorial analysis. However, this analysis also provides more clarity regarding insights not easily demonstrated through representative scenario analyses. The analysis emphasizes how understanding the interactions between these technologies and their impacts on the cost of abatement can help better inform energy policy decisions.

The third essay presented in Chapter 4 focuses on the impact technological change has on the cost of abatement, but with a special attention paid to the issue of delayed technology development. By combining the probability of advanced technology success estimates from expert elicitations with the abatement cost data estimated with an integrated assessment model, a stochastic dynamic programming model is developed. The goal of this model is to derive the optimal R&D strategy maximizing reduction in the expected total abatement cost of meeting a hypothetical limit on the atmospheric CO_2 level. A multi-period extension of the model allows intertemporal dynamic optimization where the policy-maker can select the technologies to be invested in immediately and the technologies to be invested in later. The results indicate that some technologies are more sensitive to delays in their development, while others are robust in their impacts. The analysis emphasizes the benefit of having a wait-and-see option that lets the policy-maker further optimize upon the observation of successes and failures of prior investments.

The three essays collectively serve to demonstrate the importance of clearly understanding the differences among low-carbon technologies. They also provide methodological foundations upon which such technologies can be assessed and compared. Combining these methods with an enhanced understanding of the technologies will

contribute to the body of research aimed at minimizing the cost of mitigating climate

change.

Chapter 2: The Impact of Technological Change on the Marginal Cost of Greenhouse Gas Abatement

2.1. Introduction

This chapter addresses the question of how advancement in an energy technology impacts the cost of CO_2 abatement. From the impact of technological change process depicted in Figure 1.1, this essay particularly focuses on how each given technological change reduces the abatement cost through changes in the energy market equilibrium. Figure 2.1 stylistically shows this sub-process in terms of energy market equilibrium. The left panel shows how the equilibrium production level of each individual energy technology is determined in the energy market at any given level of energy supply. A simple equal marginal cost rule[3] determines this equilibrium throughout the market.
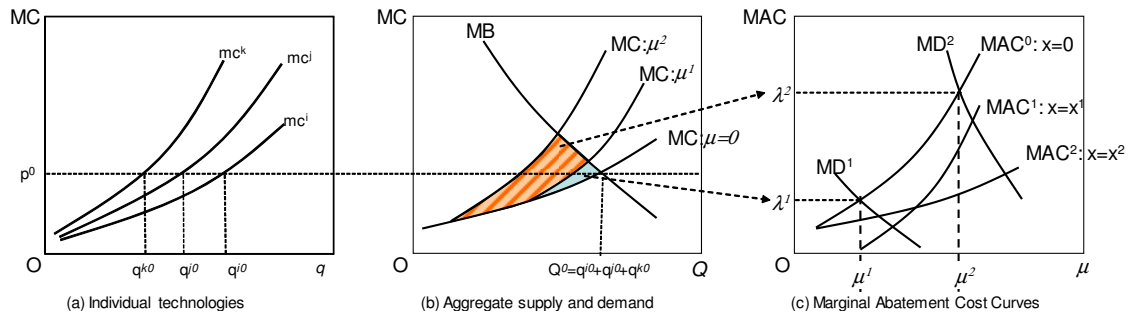
*note: $0 < \mu^1 < \mu^2$

Figure 2.1: The market dynamics of technological change and GHG abatement

The marginal cost curves of each technology jointly determine the aggregate energy supply curve in the middle panel. This panel also shows how the supply curve changes as CO_2 abatement constraints restrict the amount of fossil fuel used in the

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[3] Note that in this highly stylistic illustration, marginal cost curves not only represent financial costs, but also represent all conceivable non-financial costs, including institutional constraints on deployment. For instance, the inability to expand nuclear power due to public opposition would be represented as an infinitely inelastic marginal cost curve.

economy. The market clearing price of the energy market equilibrium is determined at the point where the aggregate marginal cost curve (supply curve) intersects the marginal benefit curve (demand curve).

The marginal welfare reduction[4] corresponding to each incremental abatement level can be represented as a marginal abatement cost (MAC) curve in the right panel. This panel also shows two different possible marginal damage (MD) curves, as well as two additional MAC curves for two different types of technological change: one pivoting downward, the other shifting downward. The equilibrium abatement level is determined at the point where the marginal damage equals the marginal abatement cost. This panel shows how technological changes affect the equilibrium abatement level, as well as the equilibrium shadow cost of emission (which equals the optimal CO_2 tax or the market price for the emission permit in case of a cap-and-trade permits system).

The importance of accurately representing the impact of technological change on the MAC curve is depicted in this panel. If a policy maker is facing a choice between the technological changes X^1 and X^2 under an impending carbon pricing regime, X^2 is obviously the better choice in the high damage case, in every aspect.

However, in the lower damage case, while the shadow cost and the optimal abatement level are the same for both technological changes, the comparison of the integrated area under the MAC curves shows that X^1 has a larger value in terms of reduction in the total abatement cost. Notice that a simple MAC reduction *magnitude* at the level of equilibrium abatement does not yield sufficient information to estimate the

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[4] This reduction is a *gross* reduction, not accounting for foregone climate damages. I intentionally avoid using a much common term "deadweight loss", as it may mislead the readers into thinking there would be a *net loss* to the society from a climate policy. In theory, a socially optimal climate policy would be designed to *correct* market failure of CO_2 emission externalities, and hence would result in a *net gain* to the society.

value of a technological change. Understanding the *pattern* of MAC curve reduction, as well as the *magnitude,* is the key to better estimating the value of technologies. This insight is even more valuable when one considers that the marginal damages, as well as successes in technology developments are, in fact, uncertain.

This essay focuses on understanding the energy market mechanisms that determine the way the MAC curve changes with respect to technological change. In the following section, I review climate change literature representing MAC curves and their movements induced by technological change. In Section 2.3, I develop a formal analytical framework for characterizing the impact of technological change on the MAC curve by assessing individual technologies and their interactions in the energy market. I first derive the necessary conditions for energy market equilibrium, and then derive the MAC function, defined as gross welfare loss with respect to the abatement constraint. Second, I introduce technological change into the market and identify the conditions that induce larger reductions in the MAC curve. In Section 2.4, I present heterogeneous examples of the MAC curve reductions induced by technological change, and explain the differential impacts on the curve using the analytical framework established in Section 2.3. I conclude the essay by emphasizing the importance of understanding the heterogeneous nature of technological changes affecting the MAC curve, and how such an understanding can better inform technology R&D policy and climate stabilization policy.

2.2. Literature Review

The reduction in marginal abatement cost (MAC) is one of the principal measures used to represent technological change in various types of analyses in the climate change literature. First and foremost, MAC, or the integrated area under the MAC curve, is used to evaluate the value of a specific technological change. Baker et al. (2008c; 2009a; 2009b; 2010) have published a series of papers combining expert elicitations and simulation modeling to analyze the impact of technological change on the cost of climate stabilization. Focusing exclusively on modeling results, Chon et al. (2007) synthesized the analyses on the three technology groups—solar photovoltaics (Baker et al. 2009a); nuclear (Baker et al., 2008c); and carbon capture and storage (Baker et al. 2009b)—and compared the distinct ways in which the technological changes in these groups of technologies affect the MAC curve. The major findings include:

1. Not all technological changes affect the MAC curve in the same way: some technologies yield large savings in low abatement levels, while others yield large savings in high abatement levels;

2. Some technologies are substitutes: e.g. advanced photovoltaic technology yields a smaller reduction in MAC in the scenario with advanced nuclear technology compared to the scenario without advanced nuclear technology;

3. Some technologies are complements: e.g. advanced photovoltaic technology yields a larger reduction in MAC in the scenario with low-cost energy storage compared to the scenario without low-cost energy storage.

They defined the *value of technology* as the difference in the integrated areas under the MAC curves of the reference scenario and the advanced scenario. They noted

that this *value* cannot be represented as a single numeric value, but rather as a function of the abatement constraint and the status of other advanced technologies. They used this value function as a measure for evaluating the effectiveness of public R&D investment in energy technologies.

Beyond its technology valuation purpose, where the major concern is the integrated area under the curve (or total abatement cost), MAC is often utilized for equilibrium analyses. One example is the different effects of policy tools on the diffusion of technological change for pollution control. It is widely acknowledged that, with regards to pollution control technology, such as low-carbon energy technology, all four market instruments—pollution tax, pollution subsidy, free permit, and auctioned permit—would induce an optimal level of technological change (innovation), under the assumption that the innovations are non-transferable (Downing and White, 1986). Furthermore, the level of technological change under market instruments is higher than the suboptimal level induced by command-and-control policy, and hence the market instruments are superior.

However, when the assumption of non-transferability is alleviated, Milliman and Prince (1989) argue that the incentives for *diffusion* of the technological change are different among the four market instruments. The intuition is as follows: the emission tax or the emission subsidy is set at a given level, such that the innovator firm has to pay (or receive in the case of subsidy) the same amount regardless of the diffusion; hence there is little incentive for diffusion. On the other hand, the auctioned permit system has a set number of emission permits, but permit price is endogenously determined in the market. After diffusion, the whole industry would have lower marginal abatement costs such that

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they will drive down the auctioned permit price. Thus, after diffusion, the innovator firm,

as well as non-innovator firms, will pay less per permit, such that the innovator firm

would have higher incentive to diffuse the invention. The assumption on MAC reduction

plays a central role in this analysis: the extent of diffusion incentive is largely dependent

on the magnitude of MAC reduction.
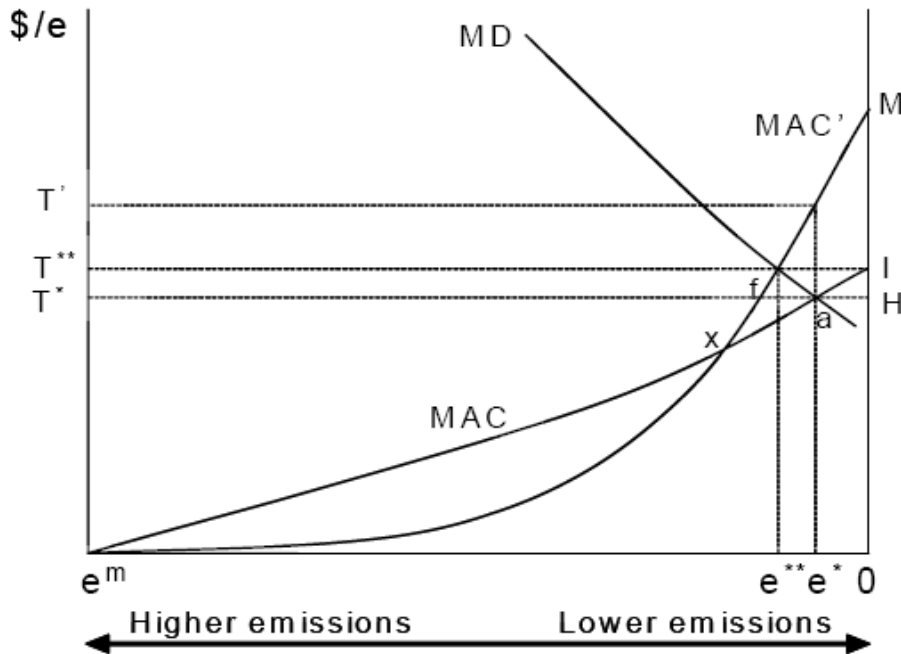
Figure 2.2: A model of technological change in pollution control
Reproduced from Baker et al. (2008a)

Baker et al. (2008a) added a special example of technological change using the

same framework of Milliman and Prince (1989). Instead of advanced technology

reducing the marginal abatement cost curve throughout abatement level, their example

included marginal abatement cost at high levels of abatement increasing due to

technological change. This counter-intuitive phenomenon can be observed from what

they call proportional emission reduction technology. One of the examples they give is the thermal efficiency increase in the fossil fuel powerplant. Initially, higher efficiency lowers the MAC. But as the abatement constraint reaches 100%, the total abatement costs are equal in the reference and advanced cases, as all fossil fuel powerplants must be driven out of the system.[5] The equality of total abatement costs at 100% abatement, combined with lower MAC at the lower abatement level, results in a higher MAC at the higher abatement level. In this particular group of technologies and at sufficiently high abatement levels, the firm incentive for technology diffusion is the lowest in the auctioned permits case, since the diffusion of technology would result in a higher permit cost. Accurately representing the change in MAC with respect to technological change is the key to determining the best market instruments for technology diffusion.

MAC is also crucial at determining the optimum intertemporal abatement path. Goulder and Mathai (2000) analyzed how the presence of induced technological change (ITC) would affect the optimal abatement path, as well as the optimal CO_2 tax path. They analyzed four scenarios based on whether the source of ITC is from R&D or from learning-by-doing (LBD) and whether the climate stabilization policy is based on cost-effectiveness or net benefit maximization. The results of the analysis indicate that the tax trajectory would fall in all four cases, while the abatement path "steepens" in R&D cases but is ambiguous in LBD cases.

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[5] They assumed no availability of negative-emission technologies. If negative-emission technologies -- such as biomass-fired powerplant with carbon capture and storage – are available, not all fossil fuel would need to be driven out of the system.

Cost-Effectiveness Case
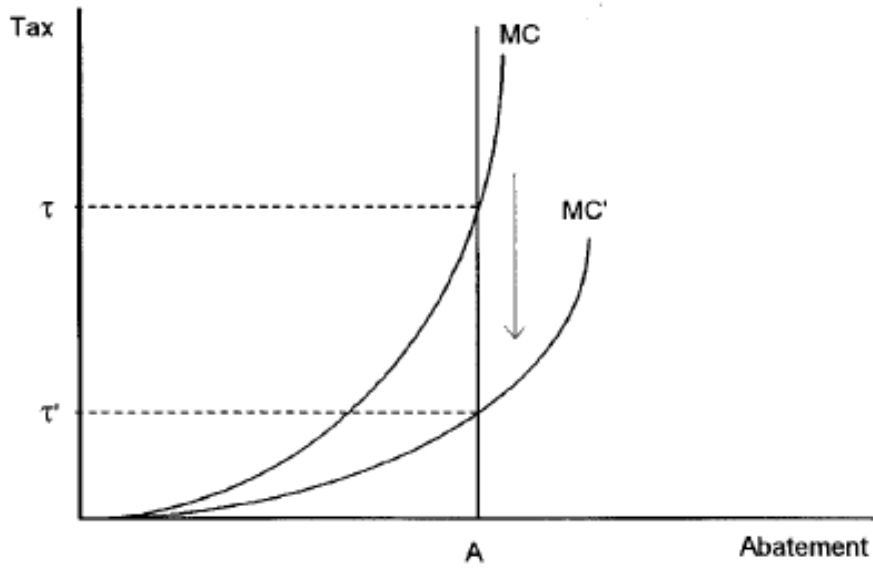
Benefit-Cost Case
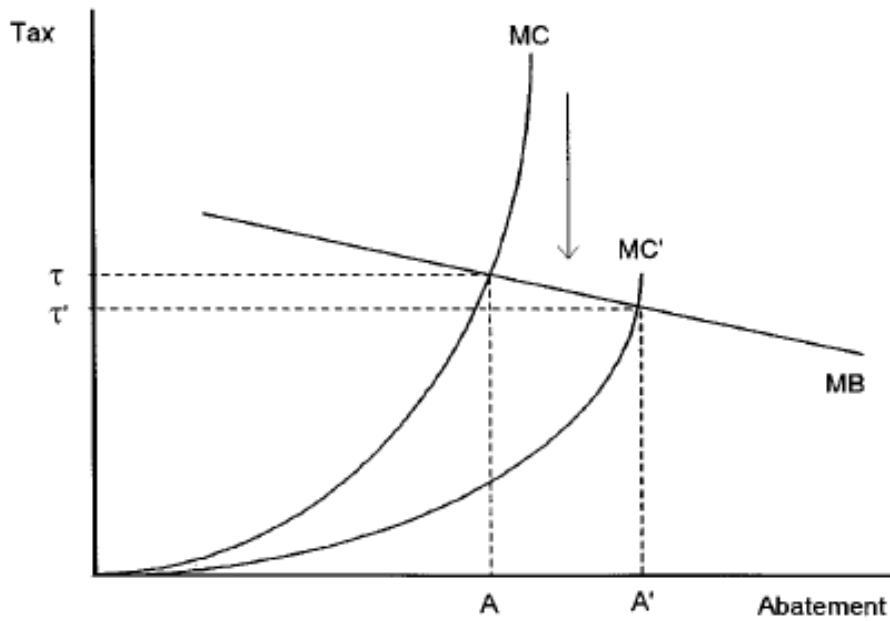
Figure 2.3: Optimal climate policy in a static setting
Reproduced from Goulder and Mathai, (2000)
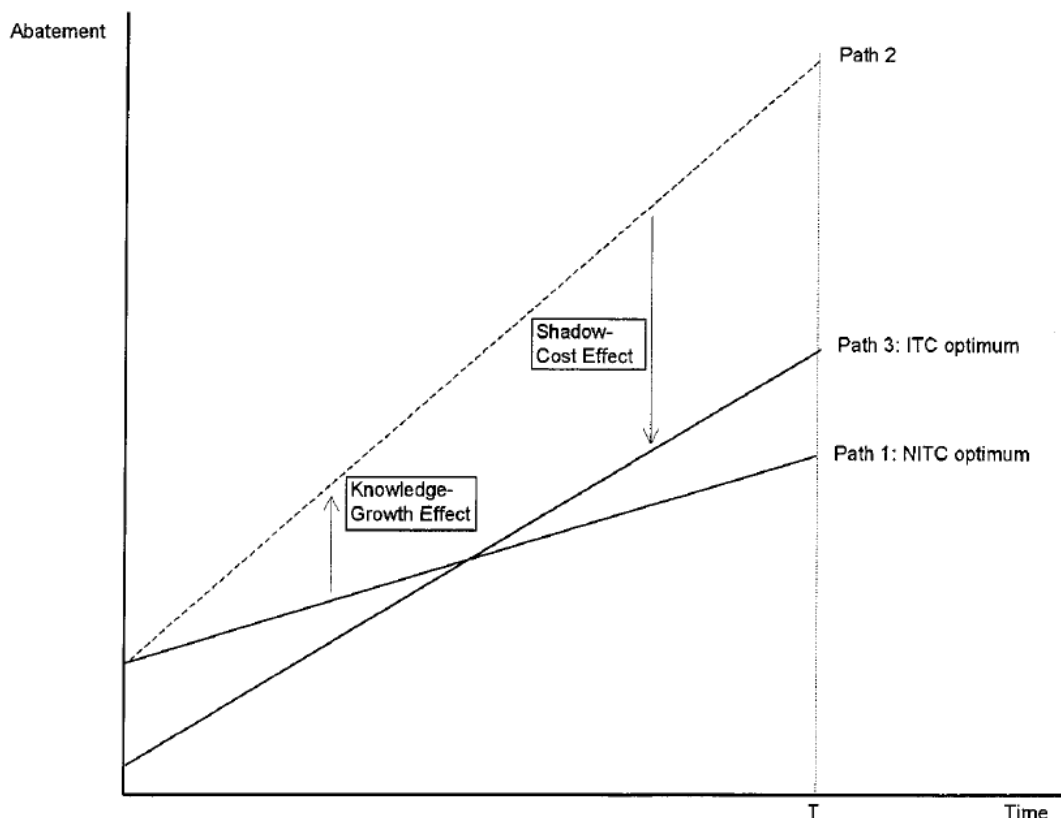
Figure 2.4: Knowledge-growth and shadow-cost effects
Reproduced from Goulder and Mathai, (2000)

The logic of the "steepening" of the abatement path is that since R&D lowers the

MAC in the future, the future abatement level can be higher with the same abatement cost

(knowledge-growth effect in Figure 2.4). However, in the cost-effectiveness case, only a

fixed amount of abatement is required (Figure 2.3), and thus the shadow cost of emission

is reduced, leading to lower abatement in the earlier periods (shadow-cost effect). The

ambiguity of the effect of LBD on the abatement path arises from the fact that while

MAC in the future would be reduced by LBD, and hence a higher abatement in the future

is justified, the level of LBD is at the same time a function of earlier abatement activity

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(hence the "learning"), and higher abatement activity in the earlier period is also desirable. Thus, the relative magnitude of the trade-offs determine the abatement path.

While the general direction of the impact is only dependent upon the *direction* of MAC curve change induced by the technological change, the *pattern* of change in the MAC curve is a main determinant of the magnitude of the optimal tax path and of the slope of the abatement path, as well as the direction of the effect of LBD on abatement.

The last example relates to the role of MAC in the technology R&D strategy under uncertain chance of large climate change damage. Baker et al. (2006) characterized technological change in three distinctive types reproduced in Figure 2.5. Their results show that as the probability of large climate damage increases, the optimal R&D portfolio should include a larger share of the "cost reduction" technologies, as opposed to the "emission reduction" technologies. The intuition is that with a high probability of large climate damages and a correspondingly high abatement level, cost reduction technologies perform the best as a *hedging* strategy, because the magnitude of MAC reduction is larger at the high levels of abatement.

The results of these analyses are highly dependent upon the impact of technological change on the MAC curve, and they point to the need for a better understanding of the dynamics of technological change. However, much of previous literature makes rather simplistic assumptions on how the MAC curve changes due to technological change. First, the technological changes are often represented as homogeneous aggregate phenomena, while, as will be shown in the analysis section, each specific technological change has distinctive characteristics. Second, the impact of technological change on the MAC curve is often represented as a homogenous effect,

most commonly a "pivot" (Figure 2.3; a proportional MAC reduction; Goulder and

Mathai, 2000), a parallel "shift" (Figure 2.5.B; Baker et al. 2006), or some combination

of the two. And the technological changes are only distinguished by the magnitude or the

timing.
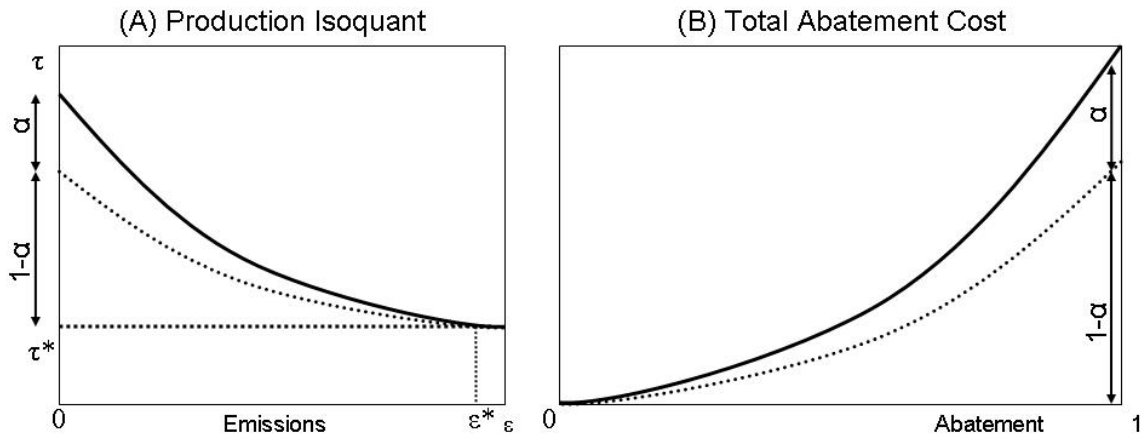
(A) Cost Reduction: The aggregate cost of energy production is proportionally reduced across all levels of abatement. The MAC curve is also proportionally reduced (pivot).
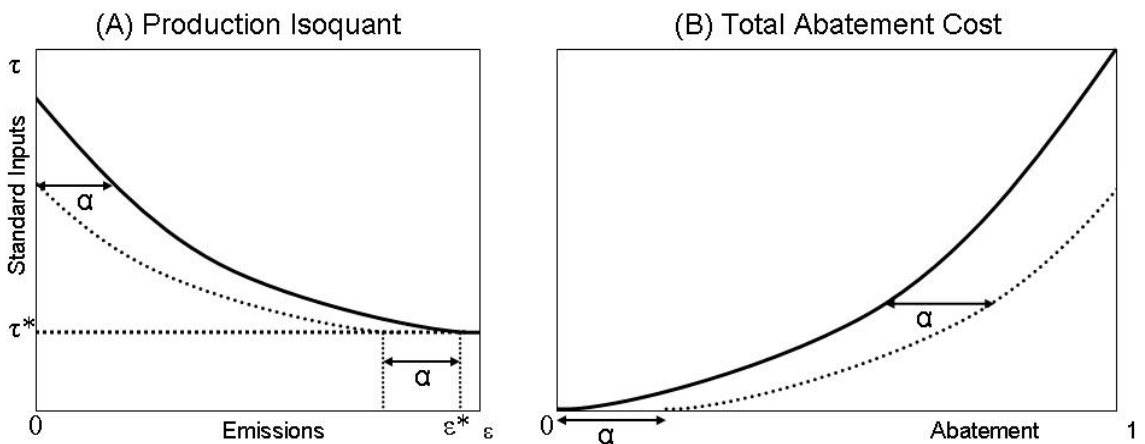
(B) Constant Emissions Reduction: A fixed amount of emission is reduced across all levels of abatement. The MAC curve shifts rightward.

(A) Production Isoquant

(B) Total Abatement Cost
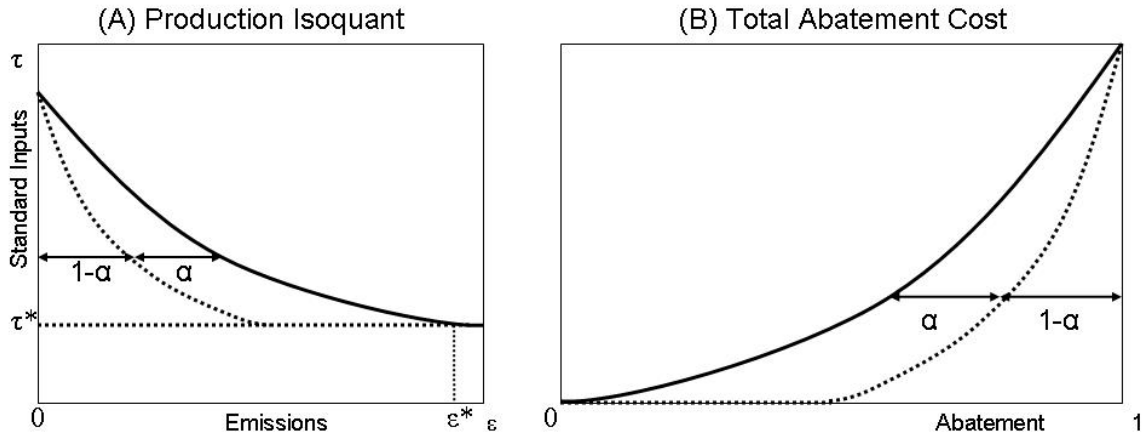
(C) Proportional Emissions Reduction: A fixed proportion of emission is reduced across all levels of abatement. The MAC curve steepens.

Figure 2.5. Three types of technological change
Reproduced from Baker et al. (2006)

	Impacts to MAC	Impacts to cost of abatement	Emissions–output ratio	Production function/profit function	
	Assumes lower MAC	Pivots down		Reduces cost/increase output of non-fossil energy	Substitutes knowledge for non-fossil or overall energy
Decreasing MAC	Fischer, Parry and Pizer (2003b) Goulder and Schneider (1999) Jung et al. (1996)	Baker and Adu-Bonnah (2008) Baker, Clarke and Weyant (2006) Montero (2002)		Baker and Shittu (2006) Popp (2006a) Gerlagh and van der Zwaan (2003, 2006) van der Zwaan et al. (2002)	Goulder and Schneider (1999) Popp (2004, 2006a) Sue Wing (2003)
	Milliman and Prince (1989) Downing and White (1986) Rosendahl (2004) Bramoulle and Olson (2005)	Goulder and Mathai (2000) Parry (1998)			
	Pivots right		Reduces emissions–output ratio	Reduces carbon content/ emissions–output ratio	Substitutes knowledge for fossil energy
Increasing MAC	Baker and Adu-Bonnah (2008) Baker, Clarke and Weyant (2006)	Nordhaus (2002) Gerlagh and van der Zwaan (2006) Buonanno et al. (2003)		Baker and Shittu (2006) Farzin and Kort (2000)	Goulder and Schneider (1999) Sue Wing (2003)

Table 2.1: Categorization of representations of technical change in a selection of papers. Some papers have multiple representations of technical change
Reproduced from Baker et al. (2008a)

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Baker et al. (2008a) have surveyed how technological changes are represented in top-down analytical models and simulation models (Table 2.1). While their focus is to identify the theoretical framework under which increasing MAC with respect to technological change is likely at high abatement levels, this table also shows how often these models rely on a singular measure to represent the variety of possible technological changes. (Note, however, that some of the models in the survey include multiple representations.)

The heterogeneous patterns of the MAC curve changes simulated in the series of papers by Baker et al. (2008c; 2009a; 2009b; 2010) show that the impact of technological change on MAC curve may not sufficiently be represented with a singular measure. For instance, Figure 2.6.A shows the MAC curves estimated by MiniCAM integrated assessment model with different photovoltaic (PV) cell technologies available in 2050 (Baker et al. 2009a). From the scenario with no advancement in current PV technology (36¢/kWh 20% limit) to PV cost reduction scenarios (3¢/kWh; 5¢/kWh 20% limit), the change in the MAC curves can be best represented as a "constant shift down". However, the storage cost reduction scenarios (3¢/kWh; 5¢/kWh free storage) not only shift down the MAC curve, but also do so at an increasing rate with respect to the abatement level (right panel).

Figure 2.6.B shows an example that clearly illustrates the differences in the impacts of advanced technologies on the MAC curve. The movement of the MAC curve between No-CCS and ADV-CCS represents the introduction of carbon capture and storage in the energy market, which effectively "pivots down" the MAC curve—

increasing reduction with respect to abatement level. On the other hand, the impact of

cost reduction in a nuclear powerplant technology, represented by the movement between

REF-Nuclear and ADV-Nuclear, is better characterized by a combination of shift and

pivot down --with the pivot factor less prevalent compared to the CCS case.
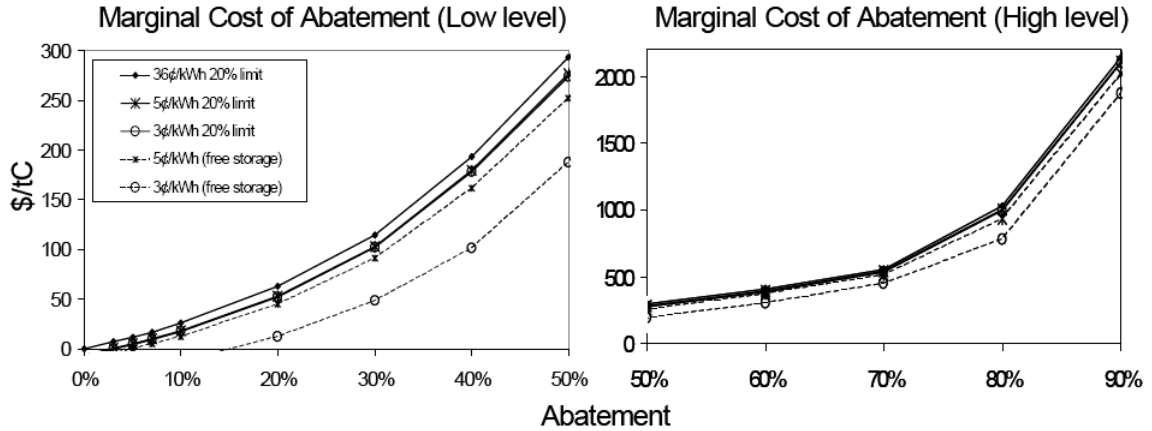
(A) MAC curves under different photovoltaic technology assumptions. The left and right panels show the MAC for abatement between 0%-50% and 50%-90% for emphasis
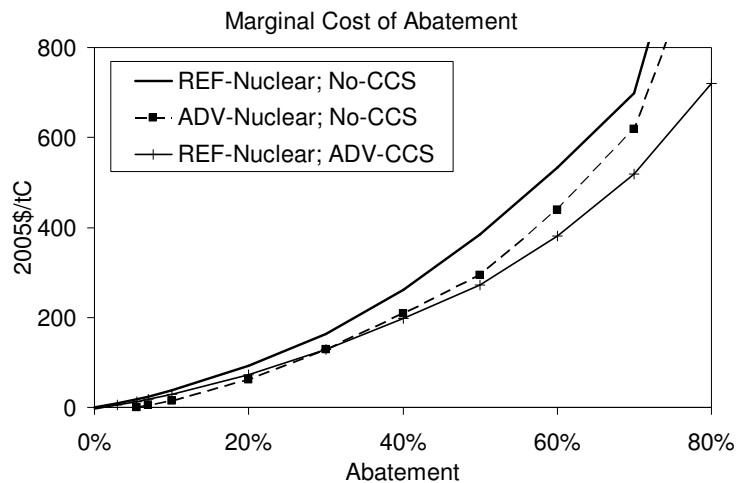
(B) MAC curves under different nuclear and CCS technology assumptions

Figure 2.6: The 2050 MAC curves simulated under different technology assumptions. Reproduced from Baker et al. (2009a) and Chon et al. (2007).

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These two examples emphasize some of the potential shortcomings of representing technological change by a singular aggregate metric. Failure to accurately represent the impact of technological change could misinform technology policy or climate stabilization policy by either overestimating or underestimating expected returns to R&D investment.

What are the factors that characterize the different pattern of changes in the MAC curve with respect to technological change? The following analysis section attempts to answer this question in a formal analytical framework. Enhanced understanding of the impact of technological change on the marginal abatement cost curve can help more accurately represent the technological change in top-down models, and in turn, better inform technology R&D policy and climate stabilization policy.

2.3. Analytical Framework

In this section, I develop a formal analytic framework to explain the impact of technological change on CO_2 abatement cost. First, I set up the framework in a general form and present associated assumptions and definitions. Second, I reduce the framework space into a readily interpretable scale with three technology groups: the generic fossil energy group that represents the aggregate of all CO_2 emitting technologies, the non-fossil technology group that undergoes technological change, and the other technology group that includes all other non-fossil technologies. I derive the energy market equilibrium conditions for the three technologies. Third, I introduce a technological change in the system, and show how the change affects the equilibrium conditions. Fourth, I analyze the conditions determining the level of initial abatement induced by

technological change. Fifth, I analyze the conditions determining the magnitude of

reductions in the marginal abatement cost induced by the technological change.

2.3.1. General Setting

This subsection describes the general framework under which my analysis will be

conducted. First, I define the optimization condition for the baseline energy mix under no

abatement constraint. Second, I introduce the abatement constraint and define

optimization conditions under the constraint. Third, I define marginal abatement cost and

express it in terms of benefit and cost functions.

The analytical framework developed here is highly abstract and follows textbook

microeconomic assumptions. It is a single period model and does not explicitly address

temporal dimensions of the issue.[6] The energy produced in the system is instantaneously

consumed, and the corresponding benefits and costs are realized. Such simplification

provides the opportunity to derive easily interpretable results. On the other hand, the

framework overlooks the possibility of act-and-learn strategy addressed in Chapter 4.

Another simplifying assumption is a perfectly competitive energy market without any

market failure other than the greenhouse gas effect. While gaining clear interpretability,

this assumption sacrifices addressing existing oligopolistic behavior in the energy market.

The baseline energy production level is defined as the equilibrium level of energy

production in the absence of a CO_2 abatement policy. The energy market clears when the

net benefit from energy consumption/production is maximized.

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[6] This setup can also be thought of as a perfect foresight model with time dimension, where energy quantity
and prices are measured in the initial period equivalent units—e.g. the amount of energy that on average
provides the equivalent benefit of one kWh in 2010.

$$\max_{q^i} B(Q) - \Sigma c^i(q^i) \qquad (1)$$

$$where, \qquad Q = \Sigma q^i \qquad (2)$$

q^i represents the amount of energy produced by each technology i, and Q represents the

aggregate level of energy consumption. $c^i(q^i)$ represents the total cost of producing q^i

amount of energy by each technology. Each energy producing technology—e.g. *coal,*

solar, biomass, etc.—is denoted with a superscript.

Assuming every technology in the market is producing a strictly positive amount

of energy; i.e. $q^i > 0$ for all *i,* the first order conditions for the maximization imply[7]:

$$\frac{\partial B(Q)}{\partial Q} = B_Q(Q) = c_q^i(q^i) = \frac{\partial c^i(q^i)}{\partial q^i} \qquad \forall i$$

Assuming strict convexity on each cost function and strict concavity on the

aggregate benefit function, there exists a unique combination of q^{i0} that solves the net

benefit maximization problem.[8] This combination is the baseline energy mix under no

carbon policy.

Now I introduce an emission abatement constraint:

$$s.t. \qquad \varepsilon q^f \leq \varepsilon q^{f0} - \mu \qquad (3)$$

$$where, \quad \mu \in \left[0, \varepsilon q^{f0}\right]$$

μ is the abatement level that takes value between zero and the total emission level at the

baseline energy mix. Superscript f denotes a generic fossil energy production technology.

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[7] I follow the convention of denoting a partial derivatives with a subscript.
[8] The nature of energy technologies utilizing scarce resources imply that the strict convexity assumptions may indeed apply. However, depending on how one defines a "technology", there may be non-convex portions of a cost curve. For instance, an individual wind farm may face decreasing marginal cost once adequate transmission and distribution capacity is fulfilled. The convexity assumptions are more applicable to an aggregate group of similar technologies where such saturation effects are averaged out.

For simplicity, I assume each unit of fossil energy emits fixed amount of CO_2 with an emission coefficient of ε (e.g. tons of carbon per GJ).

The net benefit maximization problem becomes:

$$\max_{q^i} B(Q) - \sum c^i(q^i) \tag{1}$$

$$s.t. \quad \varepsilon q^f \leq \varepsilon q^{f0} - \mu \tag{3}$$

Expression (1) indicates the objective is to maximize the net benefit from producing energy. Expression (3) constrains the level of emission to be no greater than the constraint imposed. The Lagrangian and the corresponding first order conditions are:

$$L = B(Q) - \sum c^i(q^i) + \lambda(\varepsilon q^{f0} - \varepsilon q^f - \mu) \tag{4}$$

F.O.C.s:

$$B_Q(Q) = c_q^i(q^i) \quad \forall i \neq f \tag{5.1}$$

$$B_Q(Q) = c_q^f(q^f) + \varepsilon \lambda \tag{5.2}$$

$$\varepsilon q^{f0} - \varepsilon q^f - \mu \geq 0 \tag{5.3}$$

Assuming strict convexity for cost functions and strict concavity for benefit functions, there exists a unique combination of $q^i(\mu)$ and $\lambda(\mu)$ that solves the cost minimization problem under the abatement constraint. $\lambda(\mu)$ is the shadow value of incremental carbon emission. It represents the additional cost inflicted by tightening the emission abatement constraint by a unit (not accounting for externalities caused by the emission). Substituting Expression (5.1) into Expression (5.2), this shadow value can be expressed as:

$$\lambda(\mu) = \frac{c_q^i(q^i(\mu)) - c_q^f(q^f(\mu))}{\varepsilon} \qquad \forall i \neq f \qquad (6)$$

Since under optimization condition (5.1) the marginal costs of all non-fossil technologies are the same, if Expression (6) is satisfied with one technology, then it would be satisfied for all other technologies. This shadow value is equal to the difference between the marginal cost of energy production for fossil and non-fossil energy production, multiplied by the inverse of the emission coefficient. In other words, it represents how much more it costs to substitute the marginal fossil energy with the non-fossil energy. I define this as the *marginal abatement cost (MAC)*, and it is equal to the optimum emission tax for achieving an abatement constraint, as well as the equilibrium price of emission quota in a cap-and-trade system.

2.3.2. The Three Technology Analysis

Depending on the boundary definition of technologies, the number of technologies present in the energy market is quite large. And each additional technology represented in the model requires one additional first order condition. Clear interpretations of the analysis quickly become difficult with a large number of first order conditions. Hence, from this subsection and on, I reduce the technology space into three groups and provide a simple framework under which the impact of technological change on the marginal abatement cost is analyzed.

The three groups of technologies represented in this section are generic fossil energy technology group, conventional alternatives energy technology group, and advanced alternative energy technology group. Generic fossil technology is denoted with superscript *f*. As defined in the previous section, this technology includes all CO_2

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emitting fossil energy—e.g. coal, oil, and gas—and is assumed to emit a fixed amount of CO_2 with emission coefficient ε. The conventional alternative technology is denoted with superscript *i*. This represents the aggregate of all non-fossil technologies except the technology that is affected by the (impending) technological change. Advanced alternative technology is denoted with superscript *j*. This represents one technology that will undergo the technological change. For simplicity, I assume only generic fossil emits carbon dioxide, and both alternatives are assumed to emit zero carbon dioxide[9]. Also, again I assume strict convexity for all three cost functions, in order to ensure an interior solution.

The modified net benefit maximization problem is:

$$\max_{q^f, q^i, q^j} B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j)$$

$$s.t. \quad \varepsilon q^f \leq \varepsilon q^{f0} - \mu$$

The Lagrangian and the corresponding first order conditions are:

$$L = B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j) + \lambda(\varepsilon q^{f0} - \varepsilon q^f - \mu)$$

F.O.C.s:

$$F^1 = B_Q - c_q^i = 0$$
$$F^2 = B_Q - c_q^j = 0$$
$$F^3 = B_Q - c_q^f - \varepsilon \lambda = 0$$
$$F^4 = \varepsilon q^{f0} - \varepsilon q^f - \mu$$

Applying the Implicit Function Theorem:

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[9] In reality, some alternative technologies do emit carbon dioxide, albeit at a lesser rate than conventional fossil energy technologies (e.g. Carbon Capture & Storage with less than 100% capture rate). And many alternative technologies may indirectly induce emissions by energy used to produce equipment or fuel (e.g. diesel fuel used for farm equipment producing biomass). However, with stringent abatement constraints, this energy may also be derived from zero-emission technologies.

$$\begin{bmatrix} B_{QQ} - c_{qq}^i & B_{QQ} & B_{QQ} & 0 \\ B_{QQ} & B_{QQ} - c_{qq}^j & B_{QQ} & 0 \\ B_{QQ} & B_{QQ} & B_{QQ} - c_{qq}^f & -\varepsilon \\ 0 & 0 & -\varepsilon & 0 \end{bmatrix} \begin{bmatrix} dq^i/d\mu \\ dq^j/d\mu \\ dq^f/d\mu \\ d\lambda/d\mu \end{bmatrix} = - \begin{bmatrix} 0 \\ 0 \\ 0 \\ -1 \end{bmatrix}$$

The equilibrium quantity, $q^i(\mu)$, and the marginal abatement cost, $\lambda(\mu)$, can be expressed as an implicit function of abatement level:

$$|\Delta| = \varepsilon^2 (B_{QQ} c_{qq}^i + B_{QQ} c_{qq}^j - c_{qq}^i c_{qq}^j) < 0$$

$$q_\mu^j = \frac{\varepsilon B_{QQ} c_{qq}^i}{|\Delta|} > 0$$

$$q_\mu^i = \frac{\varepsilon B_{QQ} c_{qq}^j}{|\Delta|} > 0$$

$$\therefore q_\mu^j / q_\mu^i = \frac{c_{qq}^i}{c_{qq}^j}$$

$$q_\mu^f = -\frac{\varepsilon (B_{QQ} c_{qq}^i + B_{QQ} c_{qq}^j - c_{qq}^i c_{qq}^j)}{|\Delta|} = -\frac{1}{\varepsilon} < 0$$

$$\lambda_\mu = \frac{B_{QQ} c_{qq}^i c_{qq}^j + B_{QQ} c_{qq}^j c_{qq}^f + B_{QQ} c_{qq}^i c_{qq}^j - c_{qq}^i c_{qq}^j c_{qq}^f}{|\Delta|} > 0$$

The production of fossil energy decreases with respect to the abatement level, while the production of both alternative technology groups increase. It is also shown that the marginal abatement cost function is an increasing function of the abatement amount. Note that the ratio of marginal production of the two alternative technologies is the inverse of the ratio of the slopes of their marginal cost functions. In other words, marginal production is larger for technologies with a marginal cost function that is less sensitive to quantity. Generally, technologies with expansion constraints have steeper marginal cost functions. Further elaborations of marginal cost functions and their sensitivity to quantity are included in the Subsection 2.3.4.

2.3.3. Introducing Technological Change

Now I introduce technological change in the advanced alternative technology and analyze the impact on MAC. Technological change can take many different forms, including an average cost reduction, efficiency increase, or resource pool expansion. In order to capture a broad range of possibilities, technological change—denoted as *x*—is represented in a general form: $c^j(q^j, x)$. Technological change is specified as changes that *lower* the cost function of advanced alternative technology *j* in any form:[10]

$$c_x^j = \frac{\partial c^j(q^j, x)}{\partial x} \leq 0$$

$$c_{qx}^j = \frac{\partial c_q^j(q^j, x)}{\partial x} = \frac{\partial^2 c^j(q^j, x)}{\partial q_j \partial x} \leq 0$$

The change in cost function brought on by the technological change, in turn, affects the optimal production of each technology. The maximization problem in three technology framework with technological change becomes:

$$\max_{q^f, q^i, q^j} B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j, x)$$

$$s.t. \quad \varepsilon q^f \leq \varepsilon q^{f0} - \mu$$

I distinguish two components of the impact of technological change on abatement cost (Figure 2.7). The first component is the technology-induced *initial abatement* at non-binding emission constraint (hereafter *initial abatement*). When a technological change sufficiently reduces the cost of advanced alternative, it drives out some level of fossil

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[10] In reality, technological changes may take different forms. For instance, a new nuclear reactor design may increase the safety of the reactor, while driving up the operating cost. Such cases are not explicitly addressed here. However, by reducing every aspect of the technology into a single cost curve, we can theoretically formulate such cases in the same framework. For instance, a financially low-cost nuclear reactor facing institutional barriers to deployment can be represented with an infinitely inelastic marginal cost curve. A new reactor design that allows expanded deployment through improved safety could be represented with a high marginal cost, but still being less than infinity, hence satisfying the definition of "technological change" used in this analysis.

energy solely by price competition, *without* the confounding effect of the emission

constraint. The second component is the reduction in the marginal abatement cost when

the abatement level is high enough, such that the constraint is binding, and hence the

shadow value of CO_2 emissions would be positive.
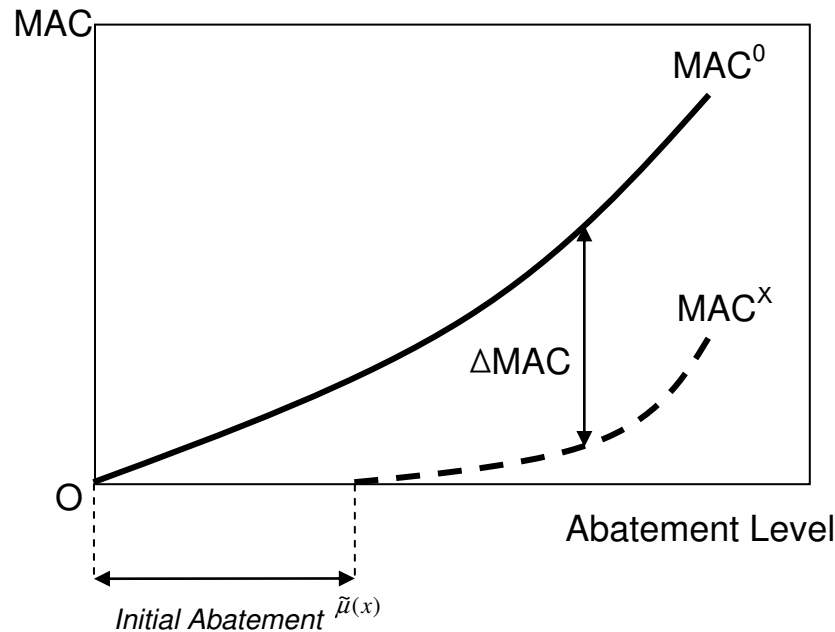
Figure 2.7: Two components of the impact of technological change on the MAC

2.3.4. Technology-Induced Initial Abatement in the Case of a Non-Binding Emission Constraint

The level of initial abatement can be derived by solving the maximization

problem for fossil energy quantity with the abatement constraint set to zero. This answers

the question of what amount of GHG emissions will be abated solely due to technological

change without the abatement constraint. For example, a cost reduction in the advanced

alternative technology will increase the optimal production of the technology, and thus

reduce the optimal production of fossil energy. This equilibrium effect, in turn, reduces emissions even without abatement constraint. With the abatement constraint non-binding, the maximization problem (1) becomes:

$$\max_{q^f, q^i, q^j} B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j, x)$$

F.O.C.s:

$$F^1 = B_Q - c_q^i = 0$$
$$F^2 = B_Q - c_q^j = 0$$
$$F^3 = B_Q - c_q^f = 0$$

Under the assumptions of strict convexity for cost functions and strict concavity for benefit function, the unique combination of $\{q^i(0,x), q^j(0,x), q^f(0,x)\}$ that solves the maximization problem can be expressed as the implicit function of technological change, x.

$$\begin{bmatrix} B_{QQ} - c_{qq}^i & B_{QQ} & B_{QQ} \\ B_{QQ} & B_{QQ} - c_{qq}^j & B_{QQ} \\ B_{QQ} & B_{QQ} & B_{QQ} - c_{qq}^f \end{bmatrix} \begin{bmatrix} \partial q^i / \partial x \\ \partial q^j / \partial x \\ \partial q^f / \partial x \end{bmatrix} = - \begin{bmatrix} 0 \\ -c_{qx}^j \\ 0 \end{bmatrix}$$

Solving for $\{q^i(0,x), q^j(0,x), q^f(0,x)\}$, we get:

$$|\Delta| = B_{QQ} c_{qq}^i c_{qq}^j + B_{QQ} c_{qq}^j c_{qq}^f + B_{QQ} c_{qq}^i c_{qq}^f - c_{qq}^i c_{qq}^j c_{qq}^f < 0$$

$$q_x^i = c_{qx}^j \left(\frac{B_{QQ} c_{qq}^f}{|\Delta|} \right) \leq 0$$

$$q_x^j = c_{qx}^j \left(\frac{c_{qq}^i c_{qq}^f - B_{QQ} c_{qq}^i - B_{QQ} c_{qq}^f}{|\Delta|} \right) \geq 0$$

$$q_x^f = c_{qx}^j \left(\frac{B_{QQ} c_{qq}^i}{|\Delta|} \right) \leq 0$$

The production of fossil energy and conventional alternative energy decrease with respect to the technological change on the advanced alternative energy. The production of advanced alternative energy increases with respect to the technological change.

Since the level of initial abatement ($\tilde{\mu}(x)$) given technological change x can be defined as:

$$\tilde{\mu}(x) = \varepsilon q^{f0} - \varepsilon q^f (\mu = 0, x)$$

The change in the level of initial abatement ($\tilde{\mu}(x)$) due to technological change can be expressed as:

$$\tilde{\mu}_x = -\varepsilon q_x^f = -\frac{\varepsilon c_{qx}^j B_{QQ} c_{qq}^i}{B_{QQ} c_{qq}^i c_{qq}^j + B_{QQ} c_{qq}^j c_{qq}^f + B_{QQ} c_{qq}^i c_{qq}^f - c_{qq}^i c_{qq}^j c_{qq}^f} \geq 0 \qquad (7)$$

This Expression (7) indicates that the changes in initial abatement with respect to technological change is determined by the extent to which the marginal cost of the advanced alternative is reduced, adjusted for relative slopes of the marginal benefit function and the marginal cost functions of competing technologies. Unlike the case of binding abatement constraints, the level of initial abatement is also affected by the slope of marginal cost function of fossil energy production.

Proposition 1:

Ceteris paribus, the size of *initial abatement* induced by technological change is larger when:

1. the reduction in the marginal cost of advanced alternative energy is larger;

2. the marginal cost of advanced alternative energy is less sensitive to quantity;

3. the marginal cost of conventional alternative energy is more sensitive to quantity;

4. the marginal cost of fossil energy is less sensitive to quantity;

5. the marginal benefit of aggregate energy is more sensitive to quantity.

Concrete examples of each proposition may provide clarity. Proposition 1.1 is stating the obvious; moving from 30¢/kWh solar panels to 5¢/kWh solar panels provides larger impact than do 10¢/kWh solar panels. Propositions 1.2 and 1.3 address the relative curvatures of the marginal cost curves. Typically, expansion constraints on a technology induce high sensitivity to quantity. In an extreme example, nuclear reactor technology in the countries that legally limit the amount of nuclear reactors would face an infinite marginal cost beyond the legal limit. Proposition 1.2 is stating that the same low-cost nuclear reactor technology will have a larger impact in the countries without legal limits than the ones with legal limits. The flipside is Proposition 1.3; a low-cost solar panel technology will have a larger impact if the expansion of the competing technology (nuclear) is legally limited and hence faces rapidly increasing marginal costs.

Proposition 1.4 addresses the cost curve of aggregate fossil energy. Aside from temporary fluctuations due to political instability, extreme weather events, among others, the marginal cost of fossil energy is relatively insensitive to the quantity. Further into the future, we may observe a substantial increase in the marginal cost of crude oil, when we are nearing the exhaustion of the economically viable crude oil deposits. However, on the aggregate, unconventional oil and liquefied coal could substitute depleted crude oil, hence reducing the sensitivity of the cost to quantity. With the long-run equilibrium cost of fossil energy generally insensitive to quantity, Proposition 1.4 has little effect on the initial abatement amount.

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Proposition 1.5 addresses the aggregate demand curve for energy. The marginal

benefit being insensitive to quantity implies an elastic demand curve. There are regional

and sectoral differences in the demand curve. For example, the energy demand for

passenger transport in the countries without widespread public transit options would be

less elastic than the energy demand for freight transport, where small changes in energy

prices determine the profitability of firms.

Consider an extreme case where the energy demand is perfectly elastic; in other

words, a sector that will consume unlimited amount of energy under 10¢/kWh. Suppose

the market equilibrium before the technological change consisted of 100 units of coal and

10 units of solar. Now suppose a technological change allowed 50 units of solar to be

supplied under 10¢/kWh. The resulting market equilibrium would consist of 100 units of

coal and 50 units of solar, because the perfectly elastic sector will consume any and all

energy under 10¢/kWh. The initial abatement amount is exactly zero in this extreme

example. In an opposite case, where a sector with perfectly inelastic demand would

consume 110 units of total energy regardless of price, the resulting equilibrium could be

60 units of coal and 50 units of solar, yielding 40 units of the initial abatement. In reality,

most regions and sectors fit somewhere in between the two extremes. Proposition 1.5

states that the less elastic the demand, the larger the amount of the initial abatement.

2.3.5. The Reduction in the Marginal Abatement Cost

When the abatement constraint is no greater than initial abatement level, the

constraint is non-binding, and thus MAC is zero. However, when the abatement

constraint goes beyond the initial abatement level, the constraint is binding, and thus we

can assess the magnitude of reduction in the MAC. The maximization problem with binding abatement constraint is:

$$\max_{q^f,q^i,q^j} B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j, x)$$

$$s.t. \quad \varepsilon q^f \leq \varepsilon q^{f0} - \mu$$

The Lagrangian and the corresponding first order conditions are:

$$L = B(q^f + q^i + q^j) - c^f(q^f) - c^i(q^i) - c^j(q^j, x) + \lambda(\varepsilon q^{f0} - \varepsilon q^f - \mu)$$

F.O.C.s:

$$F^1 = B_Q - c_q^i = 0$$
$$F^2 = B_Q - c_q^j = 0$$
$$F^3 = B_Q - c_q^f - \varepsilon\lambda = 0$$
$$F^4 = \varepsilon q^{f0} - \varepsilon q^f - \mu$$

Applying the Implicit Function Theorem:

$$\begin{bmatrix} B_{QQ} - c_{qq}^i & B_{QQ} & B_{QQ} & 0 \\ B_{QQ} & B_{QQ} - c_{qq}^j & B_{QQ} & 0 \\ B_{QQ} & B_{QQ} & B_{QQ} - c_{qq}^f & -\varepsilon \\ 0 & 0 & -\varepsilon & 0 \end{bmatrix} \begin{bmatrix} dq^i/d\mu & dq^i/dx \\ dq^j/d\mu & dq^j/dx \\ dq^f/d\mu & dq^f/dx \\ d\lambda/d\mu & d\lambda/dx \end{bmatrix} = - \begin{bmatrix} 0 & 0 \\ 0 & -c_{qx}^j \\ 0 & 0 \\ -1 & 0 \end{bmatrix}$$

The equilibrium quantity, $q^i(\mu,x)$, and the marginal abatement cost, $\lambda(\mu,x)$, can be expressed as implicit function of abatement level:

$$|\Delta| = \varepsilon^2(B_{QQ}c_{qq}^i + B_{QQ}c_{qq}^j - c_{qq}^i c_{qq}^j) < 0$$

$$q_x^i = \frac{\varepsilon^2 c_{qx}^j B_{QQ}}{|\Delta|} \leq 0 \tag{8.1}$$

$$q_x^j = -\frac{\varepsilon^2 c_{qx}^j (B_{QQ} - c_{qq}^i)}{|\Delta|} \geq 0 \tag{8.2}$$

$$q_x^f = 0 \tag{8.3}$$

$$\lambda_x = \frac{\varepsilon c_{qx}^j B_{QQ} c_{qq}^i}{|\Delta|} \leq 0 \tag{8.4}$$

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The production of conventional alternative energy decreases with respect to the technological change on the advanced alternative energy. The production of advanced alternative energy increases with respect to the technological change. The production of fossil energy is constrained by the abatement requirement, and hence does not change with respect to technological change. The marginal abatement cost decreases with respect to the technological change.

Substituting Expression (8.1) into Expression (8.4) and rearranging yields:

$$\lambda_x = \frac{c_{qx}^j + c_{qq}^j q_x^j}{\varepsilon} \tag{9}$$

The first term of the numerator on the RHS represents a reduction in the marginal cost due to technological change. The cost reduction effect in Figure 2.8 shows this effect. The second term of the numerator on the RHS represents an upward movement along the marginal cost curve due to increased production of advanced alternative energy. The rebound effect in Figure 2.8 shows this effect. The resulting reduction in MAC is smaller than the nominal cost-reduction effect. As the cost reduction makes the advanced alternative technology more competitive in the market, the amount of its production increases. According to the convexity assumption on cost curves, an increase in production results in an increase in marginal cost. This rebound effect partially offsets the nominal cost reduction.

Solving the maximization problem for the MAC change with respect to technological change yields:

$$\lambda_x = \frac{c_{qx}^j B_{QQ} c_{qq}^i}{\varepsilon(B_{QQ} c_{qq}^i + B_{QQ} c_{qq}^j - c_{qq}^i c_{qq}^j)} \leq 0 \tag{10}$$

Expression (10) indicates that the impact of technological change *x* on MAC is determined by the extent to which the marginal cost of advanced alternative energy is reduced, adjusted for the relative slopes of the marginal benefit function and the marginal cost functions of competing technologies. Unlike initial abatement in the case of a non-binding emission constraint, the reduction in MAC is not affected by the slope of marginal cost function of fossil energy production.
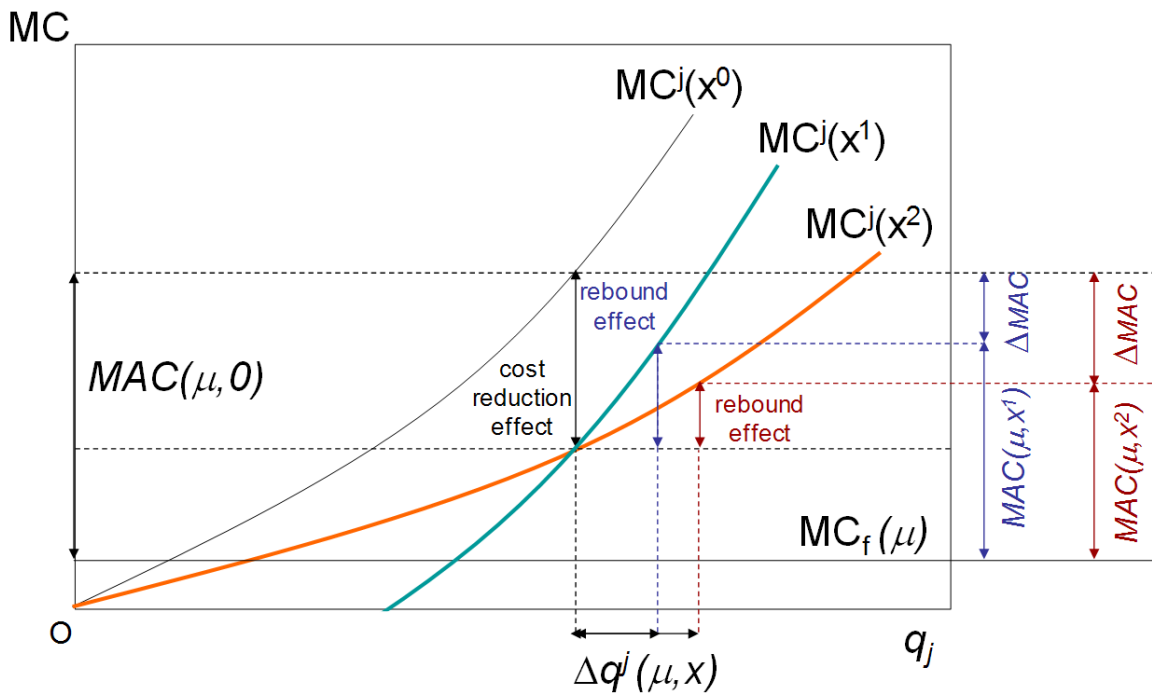
Figure 2.8: A simple discrete representation of the effect of technological change on MAC. Two distinct technological changes are shown for illustrative purposes.

Proposition 2:

Ceteris paribus, the size of reduction in MAC induced by technological change is larger when:

1. the reduction in the marginal cost of advanced alternative energy is larger;

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2. the marginal cost of advanced alternative energy is less sensitive to quantity;

3. the marginal cost of conventional alternative energy is more sensitive to quantity;

4. the marginal benefit of aggregate energy is more sensitive to quantity.

Proposition 2 is identical to Proposition 1, except for the fact that Proposition 1.4 regarding the marginal cost curve of the fossil energy is no longer relevant, because the abatement constraint effectively determined the amount of fossil energy, *regardless* of technological change in other energy forms. Thus, same logic as Proposition 1 applies here.

2.4. Applied Examples

In this section, I present some simulated examples of the MAC curve reductions induced by technological change, and explain how these reduction patterns can be related to the analytical framework established in the previous section.

First, I present the modeling assumptions used to simulate the MAC curves. Second, I analyze a batch of MAC curves under different solar photovoltaics (PV) technologies presented in Baker et al. (2009a). Particularly, I focus on the difference in the pattern of reductions in MAC between grid-integrated PVs and standalone PVs. Third, I analyze how the characteristics of *competing* technology affects the impact of a technological change, using the same advanced PV technologies under the scenarios with limited and unlimited nuclear power. Fourth, I extend the scope to include the carbon capture & storage (CCS) technologies presented in Baker et al. (2009b), and show the trade-off between two aspects of technological change: cost reduction vs. capture rate

improvement. Fifth, I compare advanced CCS technologies (Baker et al., 2009b) and advanced nuclear technologies (Baker et al., 2008c) to emphasize the heterogeneity of technological changes: one with a large *initial abatement* potential and the other with a large MAC reduction potential only under stringent abatement constraints.

2.4.1. Modeling Assumptions and Specifications

The model used for deriving MAC curves for each technology scenario is MiniCAM integrated assessment model (Kim et al., 2006; Clarke et al., 2007; Brenkert et al., 2003), which is a descendant of the model developed by Edmonds and Reilly (1985). MiniCAM and its predecessors and successors[11] have been used extensively in global climate change analyses conducted for the Intergovernmental Panel on Climate Change (IPCC), various national governments, and nongovernmental organizations.

MiniCAM links a global energy economy model and an agricultural land-use model with a suite of coupled gas-cycle, climate, and ice-melt models integrated in the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC).[12] MiniCAM tracks emissions and concentrations of greenhouse gases and short-lived chemical species.[13] The economic simulation of MiniCAM is driven by assumptions about population size and labor productivity that determine potential gross domestic product in each of 14 geopolitical regions. MiniCAM is solved by establishing market-clearing prices for all energy, agriculture, and land markets such that supplies and

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[11] The latest model description can be found at www.globalchange.umd.edu/models/gcam/.
[12] For this study I used MAGICC 4.1 (Wigley, 2003).
[13] Fifteen greenhouse-related gases are tracked: CO_2, CH_4, N_2O, NO_x, VOCs, CO, SO_2, carbonaceous aerosols, HFCs, PFCs, and SF_6. Each is associated with multiple human activities that are explicitly modeled in MiniCAM. All greenhouse gases are priced in U.S. dollars per ton of CO_2 equivalent according to their 100-year global warming potential, to ensure balance of the climate policies, but given my focus on energy technologies, I analyze only the emissions and the cost of abatement of CO_2 in this paper.

demands for all markets balance simultaneously; that is, there is no excess supply or demand for land, agricultural products, primary energy, final energy, or energy services.

MiniCAM is solved in 15-year time steps through 2095. It is a dynamic-recursive model: decisions in any period are made only with information about that period, but the consequences of decisions made in one period (resource depletion, capital stock build-up, etc.) sequentially influence subsequent periods, including the decision set available in those periods.

The MiniCAM energy system includes representations of primary energy resources, the processes involved in primary energy production and transformation to final fuels, and the employment of final energy forms to deliver energy services. Energy supplied from depletable resources—fossil fuels and uranium—depends on the abundance and grade of available resources as well as available extraction technologies. These depletable resources exhibit increasing costs in the absence of significant technological change. As the more attractive resources are consumed, less attractive resources are exploited, and, all else being equal, costs rise. Renewable resources such as wind and solar are produced from graded renewable resource bases.

Primary energy forms include oil, natural gas, coal, bioenergy, uranium, hydropower, geothermal, solar, and wind energy. MiniCAM models the transformations from these primary energy forms into the following six final energy forms: refined liquids, refined gas, coal, commercial solid bioenergy, hydrogen, and electricity. These energy forms are then used to provide end-use services in the buildings, industry, and transportation sectors.

MiniCAM is a technology-rich integrated assessment model. It contains detailed representations of technology options in all of the economic components of the system. Technology choice in MiniCAM is determined by market competition. Individual technologies compete for market share based on their technological characteristics (their efficiency in producing energy from inputs), the cost of inputs, and the price of outputs. MiniCAM uses a logit choice methodology to determine the market shares of different fuels and technologies, based on a probabilistic model of the relative prices of the competing fuels or technologies (Clarke and Edmonds, 1993; McFadden, 1974, 1981). This methodology is based on the idea that every market includes a range of different suppliers and purchasers, each of which may have different needs and may experience different local prices. Therefore, not all purchasers will choose the same technology when the average price of that technology is lower than the average price of a competing technology. The logit choice methodology allocates market shares based on prices, but ensures that higher-priced goods gain some share of the market, which is consistent with the heterogeneity observed in real markets.

The characteristics of technologies analyzed in this essay are explained in detail in the following section. All other model assumptions in this analysis are based on the version of the model used in the Climate Change Science Program (CCSP) MiniCAM reference scenario (Clarke et al. 2007).

MAC curves under each specific technology scenario were presented by plotting the levels of emissions reduction against carbon prices. First, a range of carbon price paths were created leading up to 2050. In each path, the carbon price increases over time at the discount rate, modified by the average natural system uptake rate (i.e., consistent

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with a Hotelling (1931) approach to resource extraction modified by Peck and Wan (1996)). Second, the model output emission abatement levels in 2050 were plotted on the horizontal axis against the corresponding carbon price in 2050 on the vertical axis (See Figures 2.11 & 2.13).

The future period of 2050 is chosen for this analysis of MAC for the following reasons. First, the advanced technologies I've assessed are likely to take a decade or two to be fully developed for commercial scale applications. Second, it would take a few more decades to replace the existing stock of powerplants. Four decades until 2050 gives sufficient time for the advanced technology to be fully integrated into the market.

Third, previous studies have indicated that there would be a clear divergent trend near the mid-century between low stabilization targets (e.g. 350 ppmv or 450 ppmv) and less stringent targets (e.g. 550 ppmv or 650 ppmv) (see for example, Figure 2.9 reproduced from Wigley, Richels, and Edmonds, 1996). With the residence time of CO2 in the atmosphere ranging over 100 years, the path to a low stabilization target must incorporate structural changes in the energy market towards a near steady-state level by 2050. On the other hand, a less stringent stabilization target still leaves room for slower change, with the peak emission level at or after mid-century. In the WRE scenarios (Wigley, Richels, and Edmonds, 1996), 450ppmv and 550ppmv roughly corresponds to 60% and 25% abatement levels, respectively. This difference in abatement targets may be large enough to potentially switch the ranking (in terms of the value of technology) between technologies that pivot the MAC curve and ones that shift it.
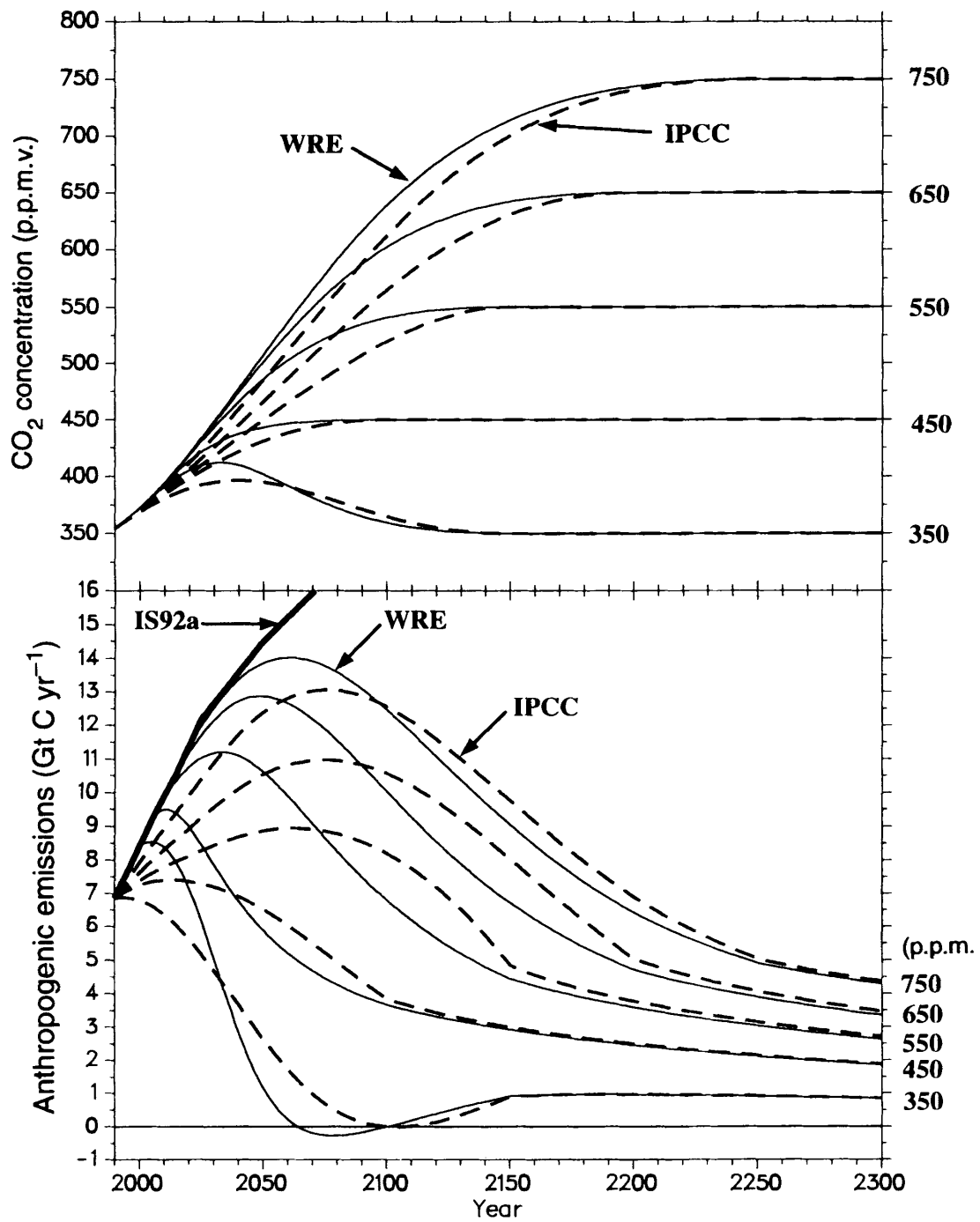
Figure 2.9: CO₂ Concentration and emission trajectories for different stabilization scenarios Reproduced from Wigley, Richels, and Edmonds (1996)

The numerical results presented in this section should be treated with caution. Particularly the results for very high carbon prices above thousands of dollars are illustrations of the effect under extreme stress in the system. An equilibrium model, such as the one used here, is typically created by an abstract representation of the system of interest. The model is then calibrated to the empirical observations on the effect of perturbation to the system, such as the effect of a gasoline price increase on the distance traveled. This methodology is suitable for modeling future gradual changes to the system that are within the same order of magnitude as the observations to which the model is calibrated. However, large-scale structural changes that are beyond the scope of empirical observations may not be effectively modeled by the same method. Such structural changes to the system may need to be exogenously specified to the model.

For instance, the results below include extremely high carbon prices up to $3000/tC, roughly equivalent to $8/gal tax on gasoline. The effects on the economy from a tripling or a quadrupling of energy prices may be fundamentally different from the nominal feedback parameter calibrated to observations from marginal changes. Thus, instead of taking the results with very high carbon prices at their face value, they should be treated as a thought experiment on how, in one possible scenario, the system might behave under extreme stress, if there had been no fundamental changes to the system. The focus should be more on the comparison across scenarios built on the same underlying system, rather than the absolute value of the results.

2.4.2. Solar Photovoltaic Technology: Limited Capacity

Baker et al. (2009a) have assessed a wide range of cost reduction in PV cells. The baseline of comparison has the cost of PV staying constant at the current level of 36 cents per kWh of electricity[14]. The lowest cost considered is 3 cents per kWh in the year 2050.

PV deployment was assessed in two different settings. First, the reference setting (20% constraint) assumes the PVs are directly connected to the existing electricity grid. Due to the intermittent nature of solar insolation, an increased share of electricity produced from PV requires backup generation capacity. The backup requirement was assumed to increase gradually with an increase in the share of PV electricity production, and reach a 1:1 backup requirement in 20% of capacity (see Figure 2.10 for a simplified representation). The backup electricity was assumed to be provided by natural gas turbines. Second, the "no constraint" setting assumes PVs come with a self-sufficient storage—such as batteries or fuel cells—thus eliminating the need for backup generation. This setting would require substantial cost reductions in energy storage technology to be competitive in the market.

Figure 2.11 shows resulting MAC curves under five different PV technology assumptions. Notice that advanced PV with a 20% constraint provides a relatively constant reduction (downward shift) in MAC throughout the abatement level, while the one with no constraint provides an increasing level of reduction (downward pivot) in MAC with respect to abatement level.

In Figure 2.12, the top panels show the electricity production technology mix under each technology scenario and the bottom panels show the difference in electricity production by each technology compared to the reference scenario with 36¢/kWh PV.

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[14] Throughout this paper I use 2005 constant dollars, unless otherwise indicated.

The bottom panels—a discrete approximation of q_x^i, q_x^j, q_x^f—clearly depict the differences between the two advanced PV scenarios. Throughout the abatement level, advanced PV with the 20% constraint case does not show much *change* in additional PV electricity production compared to the reference case. In the case of advanced PV with no constraint, on the other hand, *increasing difference* in PV electricity production with respect to abatement level is shown.

These modeling results are consistent with the analytical framework developed in the previous section. The slope of the demand function and the slopes of the MC functions of competing technologies and of fossil energy are the same in both cases. The major difference between the two advanced PV cases is the slopes of PV electricity's MC functions.
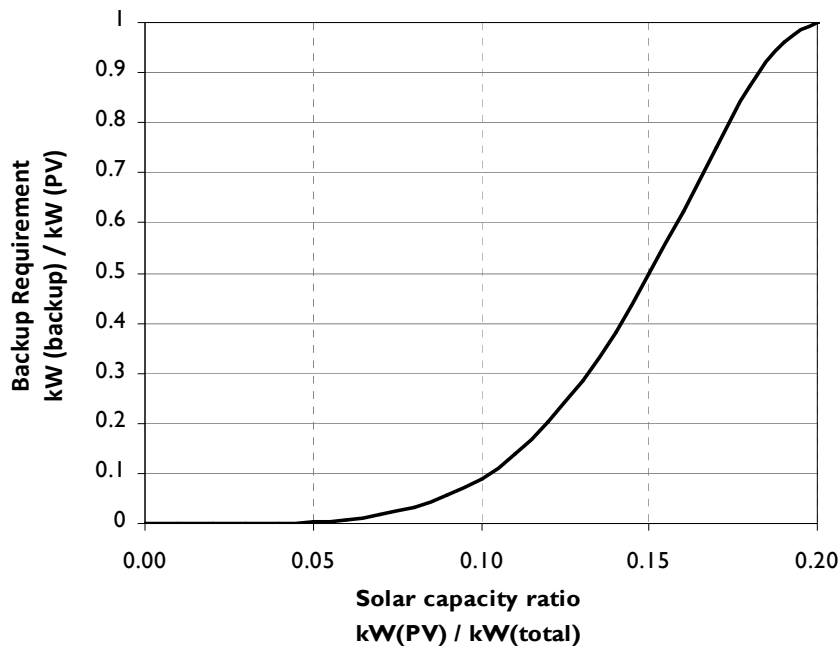
Figure 2.10: A simple representation of backup requirement
Reproduced from Baker et al. (2009a).

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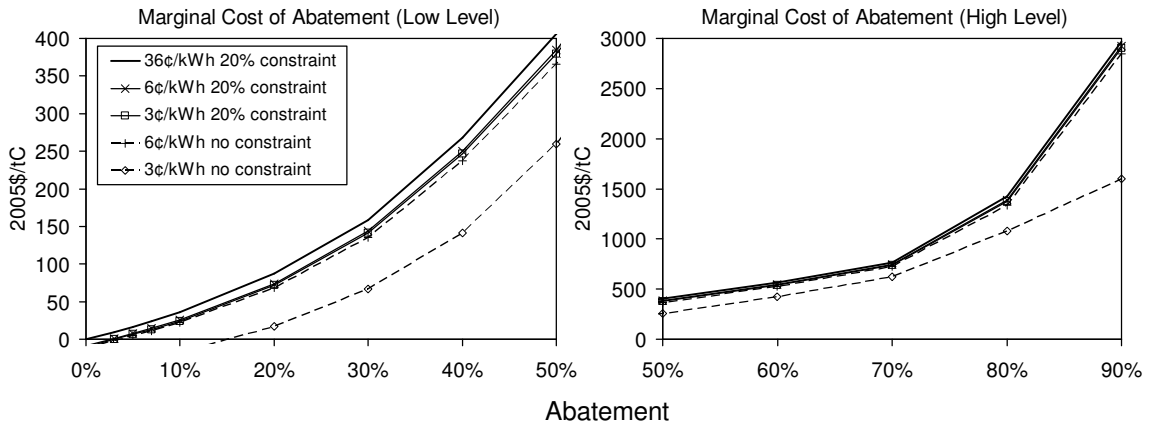
Figure 2.11: MAC curves under different PV technology assumptions. The left and right panels show the MAC for abatement levels between 0%—50% and 50%—90% for emphasis

Reproduced from Baker et al. (2009a).
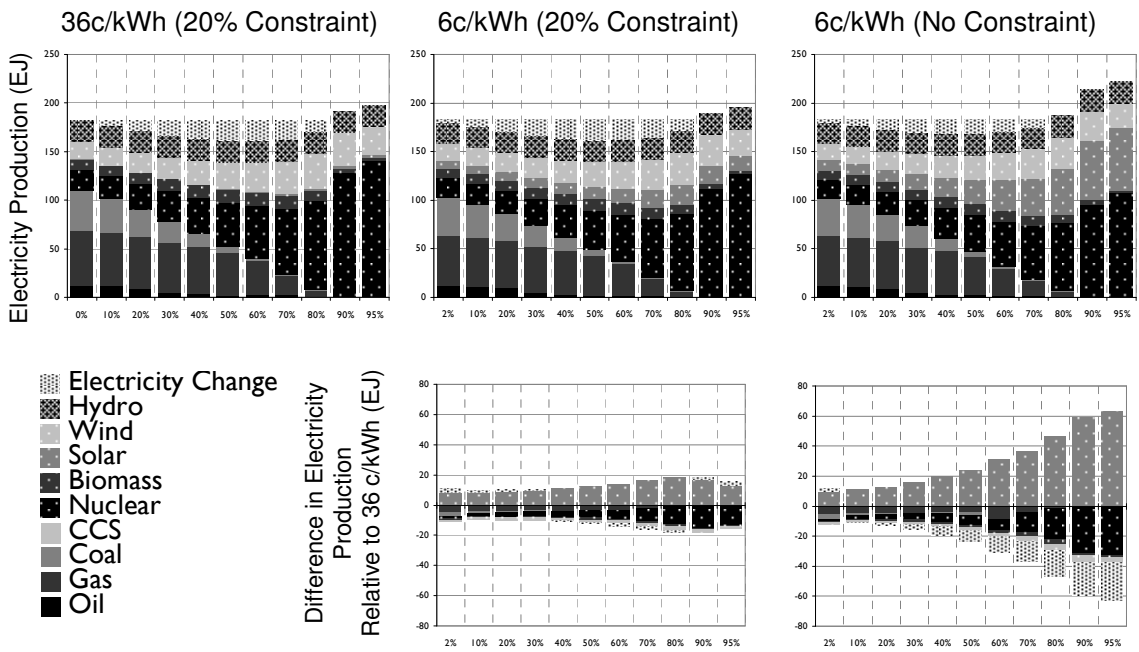
Figure 2.12: Electricity Production Technology Mix under Different Levels of Abatement

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This difference is almost non-existent at very low levels of PV deployment, because the backup requirement is minimal (Figure 2.10). This explains why the initial abatement level shows minimal difference. However, as the abatement constraint increases, the deployment of PV increases as well. This triggers backup requirements to increase, which in turn, rapidly increases the cost of deploying PV with respect to quantity and steepens the slope of MC curve. This effect, according to Proposition 2.2., results in a smaller reduction in MAC. This effect is also exacerbated at a higher abatement level, as larger PV deployment demands larger share of backup electricity (Figures 11 & 13). Thus, the MAC curves of the two advanced technologies show increasing divergence with respect to the abatement level (Figure 2.11).

2.4.3. Solar Photovoltaic Technology: Competing Technologies

The impact of technological change on the MAC is dependent upon the composition of competing technologies in the market. I show this effect by comparing the impact of low-cost PV in two different assumptions on nuclear power: one assuming freely expanding nuclear power and the other assuming a phase-out of nuclear power. Figure 2.13 shows the MAC derived for three different PV technology assumptions; the left panel with nuclear power and the right panel without. Obviously, the MAC curves are much higher in the no-nuclear scenarios, as the low-carbon technology with the largest capacity is removed. However, the focus here is on the relative magnitude of MAC reduction in the two cases. The reduction of MAC attributable to the low-cost PV is much smaller in the case with nuclear power compared to the no-nuclear case (both with the 20% constraint and without). This difference is exacerbated at the high abatement levels.
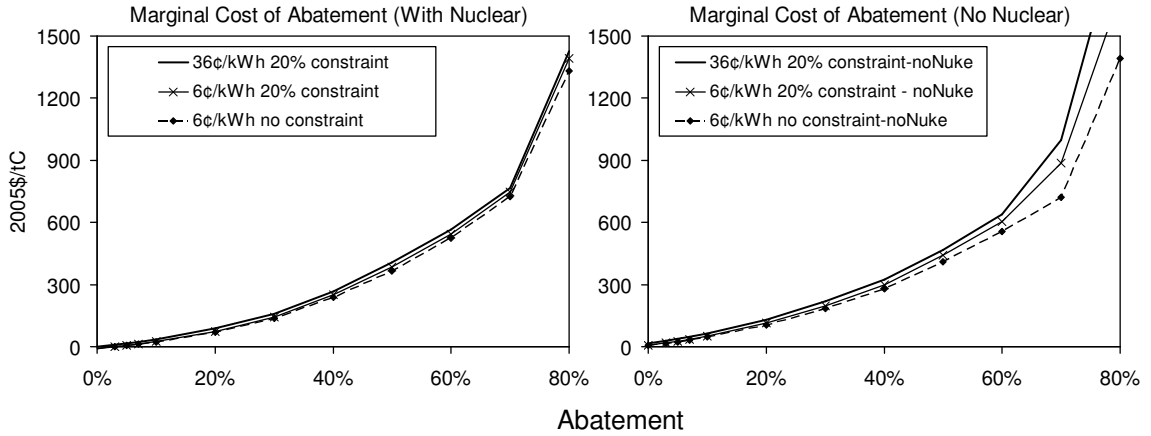
Figure 2.13: MAC curves under different PV technology assumptions. The left panel shows scenarios with nuclear power, and the right panel shows scenarios without nuclear power.
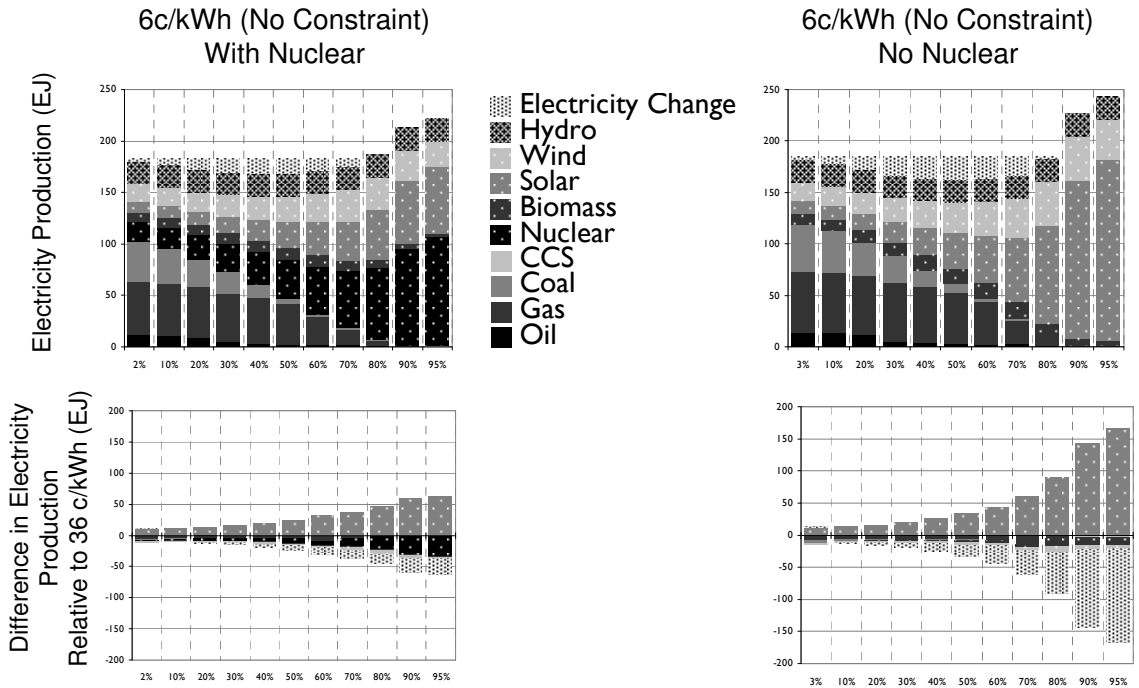
Figure 2.14: Electricity Production Technology Mix under Different Levels of Abatement. The left panels show scenarios with nuclear power, and the right panels show scenarios without nuclear power.

In Figure 2.14, the top panels show the electricity production technology mix under 6¢/kWh PV with no constraint scenarios, with and without nuclear. The bottom panels show the difference in electricity production by each technology compared to *corresponding* reference scenarios with 36¢/kWh PV. The bottom panels clearly depict the difference in the magnitude of additional PV electricity generation.

In the "with nuclear" scenarios, the nuclear power provides some of the lowest average costs of electricity at 4.8-5.7 cents/kWh, depending on the type of reactor (Clarke et al., 2006). Even the low-cost advanced PVs still have higher average costs than nuclear, and thus additional market penetration of PVs are limited to the areas better suited for PV, such as places with above average solar insolation.

In the "no nuclear" scenarios, on the other hand, low-cost PVs become one of the lowest cost alternatives available in the market. The removal of the nuclear power option effectively increases the slope of the aggregate marginal cost function of the conventional alternatives (which includes nuclear in the "with nuclear" scenario). According to Proposition 2.3., this means that the reduction in MAC as well as the increase in the deployment of advanced PV attributable to advanced PV will be larger in the "no-nuclear" case. The magnitude of this difference is exacerbated at higher levels of abatement, because the marginal cost of the conventional alternatives would increase rapidly at high production levels as the "low hanging fruits" of these technologies (e.g. hydro, onshore wind, high-yield biomass, etc.) are exhausted. This example clearly illustrates how the impact of a technological change on the MAC is highly dependent upon the composition and the characteristics of competing technologies in the market.

2.4.4. Carbon Capture and Storage: Cost vs. Capture Rate

Baker et al. (2009b) have assessed several different CCS technologies (Table 2.2). The reference case assumes that the cost of CCS technology is prohibitively high and therefore cannot be deployed on a commercial scale. Post-combustion CCS, Pre-combustion CCS, and Chemical Looping CCS technologies share the same capture rate at 90%, but energy requirements and non-energy cost of capturing CO_2 are different (from high to low in the same order.) On the other hand, Pre-combustion with High-capture technology shares the same parameters with the regular Pre-combustion technology, except the capture rate is raised to 98%. I focus on the differential impact on MAC between Chemical Lopping—characterized by low-cost low-capture-rate—and Pre-combustion High-capture—characterized by high-cost high-capture-rate.

Figure 2.15 shows MAC curves in 2050 under four different CCS technology scenarios and one scenario without CCS. Notice that the technology with the lowest MAC is switched from Chemical Looping to Pre-combustion High-capture, at around a 70% abatement level.

In Figure 2.16, the top panels show the electricity production technology mix under each technology scenario and the bottom panels show difference in electricity production by each technology compared to the regular Pre-combustion CCS scenario. The bottom panels clearly depict the differences between Chemical-looping and Pre-combustion High-capture. Chemical-looping scenario shows a gradual increase in additional CCS deployment up to the 60% abatement level, and a gradual decrease thereafter. On the other hand, Pre-combustion High-capture scenario shows virtually no difference up to the 50% abatement level and a rapidly increasing difference thereafter.

These modeling results are consistent with the analytical framework developed in the previous sections. The slope of demand function and the slopes of MC functions of competing technologies and of fossil energy are the same in both cases. The major differences between the two advanced CCS cases are the magnitudes of cost reduction and the capture rates.

Technology		Post-Combustion			Pre-Combustion			Pre-Combustion w/ High-Capture			Chemical Looping		
Fuel		Coal	Gas	Oil	Coal	Gas	Oil	Coal	Gas	Oil	Coal	Gas	Oil
Energy Requirement	MJ/kgC	4.7	10.3	7.5	2.0	4.5	3.3	2.0	4.5	3.3	0.7	1.4	1.0
Non-Energy Cost	¢/kgC	3.0	8.3	6.0	2.4	6.6	4.8	2.4	6.6	4.8	1.1	3.0	2.2
Capture Rate	%	90%	90%	90%	90%	90%	90%	98%	98%	98%	90%	90%	90%

Table 2.2: Summary of Model Parameters for the year 2050
Reproduced from Baker et al. (2009b).
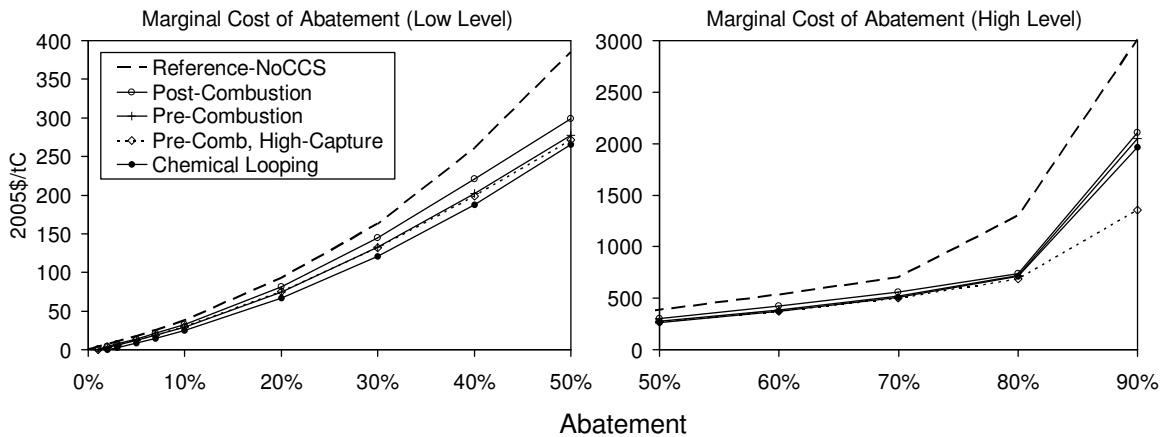
Figure 2.15: MAC curves under different CCS technology assumptions. The left and right panels show the MAC for abatement levels between 0%-50% and 50%-90% for emphasis
Reproduced from Baker et al. (2009b).
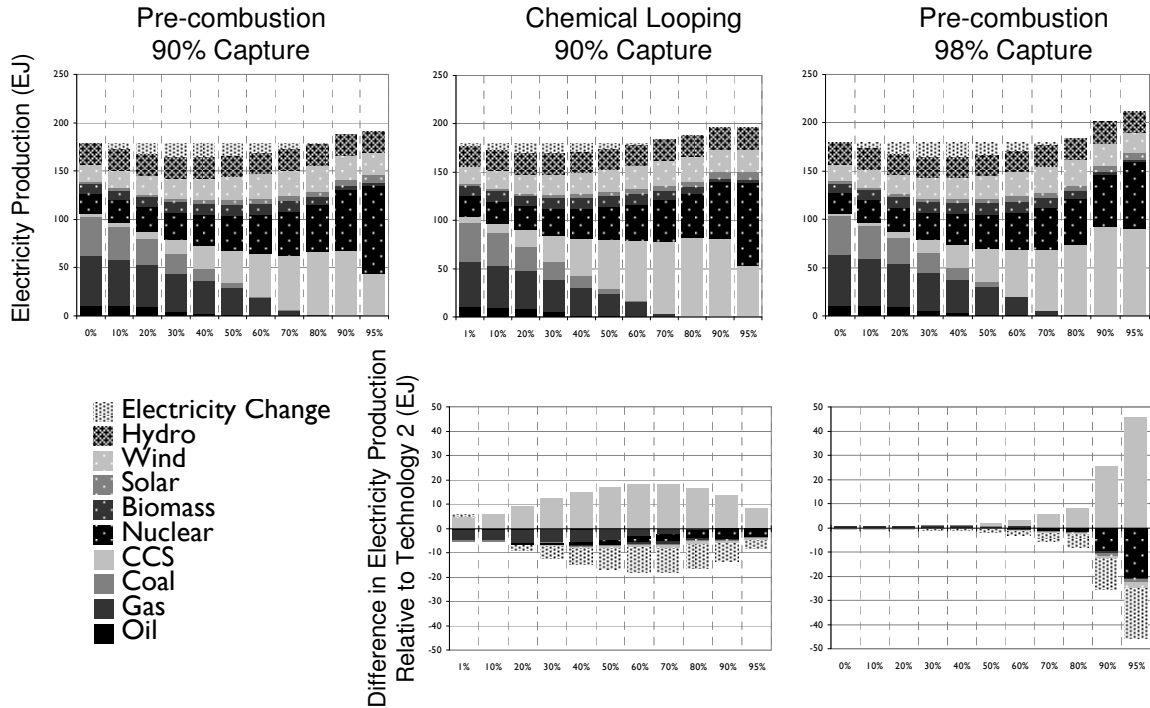
Figure 2.16: Electricity Production Technology Mix under Different Levels of Abatement

The initial abatement is virtually non-existent in both cases. No matter how low the cost of CCS becomes, it will be always higher than the same powerplant with the CCS function turned-off. Aside from small scale carbon capture to supply CO2 for industrial uses, the deployment of CCS will be minimal in the absence of abatement constraints. However, as the abatement level increases and the carbon price increases, the deployment of CCS will increase accordingly. This characteristic of CCS technologies results in a pattern of MAC reduction quite different from that of other technologies such as PV or nuclear. While most other alternative technologies will show some combination of the downward shift and pivot of MAC curves, MAC curves with CCS technologies mostly show only a downward pivot (Baker et al. 2009b).

The analytical framework expects Chemical-looping and Pre-combustion High-capture to switch their rankings in terms of the largest impact on the MAC. From Proposition 2.1., we know that *Ceteris paribus*, the size of the reduction in MAC is larger when the reduction in the marginal cost of advanced alternative energy is larger. As seen in Table 2.2, this reduction is substantially larger in Chemical-looping compared to Pre-combustion High-capture. Hence, when the differences in the relative sensitivities of MC curves (Proposition 2.2) are small at low abatement levels, Chemical-looping would have a larger reduction in the MAC.

However, the slopes of MC curves of CCS production diverge substantially in the high abatement levels. This is due to the nominal differences in less-than-100% capture rate of the CCS technologies. As the carbon price increases rapidly at high abatement levels, this cost applied to the modest 10% release of CO_2 substantially increases the marginal cost. In fact, at some very high level of abatement, some of CCS production is driven out of the market[15] (Dooley et al. 2006). This effect can be observed in the top panels of Figure 2.16. The highest production of CCS electricity is at around an 80% abatement level for Chemical-looping, while it is 90% for Pre-combustion High-capture. Given the five-fold difference in the release rate of CO_2, and hence in the impact of the carbon price, the rapidly diverging slopes of the advanced MC curves may eventually result in a crossing of the advanced MAC curves. In this example, the crossings were observed at around 70%, but the exact crossing point is highly sensitive to assumptions.

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[15] The exact point at which CCS starts being driven out of the market does not necessarily coincide with capture rate. For example, under reference technology scenarios, the transportation sector is the most difficult sector in which to reduce CO2 emissions, as existing alternatives (e.g. fuel cell vehicles) are very expensive. On the other hand, the electricity generation sector has readily available options other than CCS with zero emissions (e.g. wind, nuclear, biomass). Thus even at an abatement level less than 90%, it may be optimal to switch away from CCS to other zero emission alternatives, while allocating a larger emission quota to transportation sector.

The analytical framework assumes zero CO2 emissions for alternative technologies, and thus cannot accurately explain the low-CO2 alternative such as CCS without modifications. However, with some modifications, general insights could still be applied in explaining the distinct patterns of MAC curve change.

2.4.5. CCS vs. Nuclear: Pivot vs. Shift

In this subsection, I compare advanced CCS and advanced nuclear power technology. For advanced CCS technology, I use Pre-combustion 90% capture CCS from Baker et al. (2009b) used in the previous subsection. For advanced nuclear power, I consider a simple technological change reducing capital cost of a nuclear reactor in 2050 from \$2000/kW to \$1000/kW (Baker et al., 2008c). Figure 2.17 shows the MAC curves for each technology scenario.

The first thing to note is that CCS technology mainly induces MAC curves to pivot downward, while cost reductions in nuclear technology induces MAC curves to shift downward and, to a lesser extent, to pivot downward. As noted earlier, having CCS technology brings little initial abatement in the absence of carbon price. Advancement in nuclear, on the other hand, brings a sizeable initial abatement—in this example, about 5%. The initial abatement is large both because of large reduction in overall cost (Proposition 1.1.) and because of an assumption that the MC of nuclear power is less sensitive to the number of reactors (Proposition1.2.) so long as they are built in the regions that are favorable to nuclear power.

Marginal Cost of Abatement
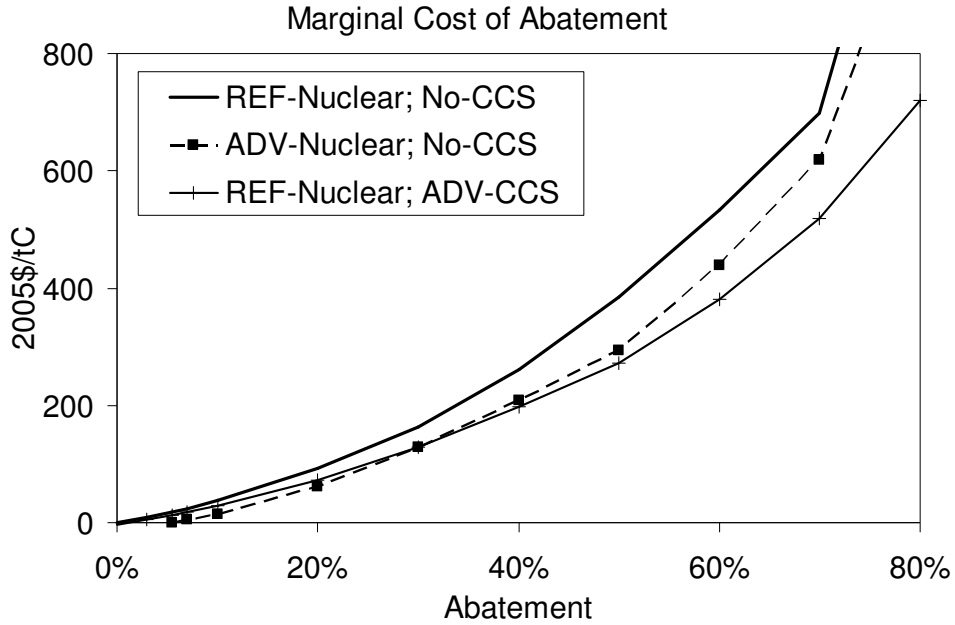
Figure 2.17: MAC curves under different CCS and Nuclear technology assumptions.
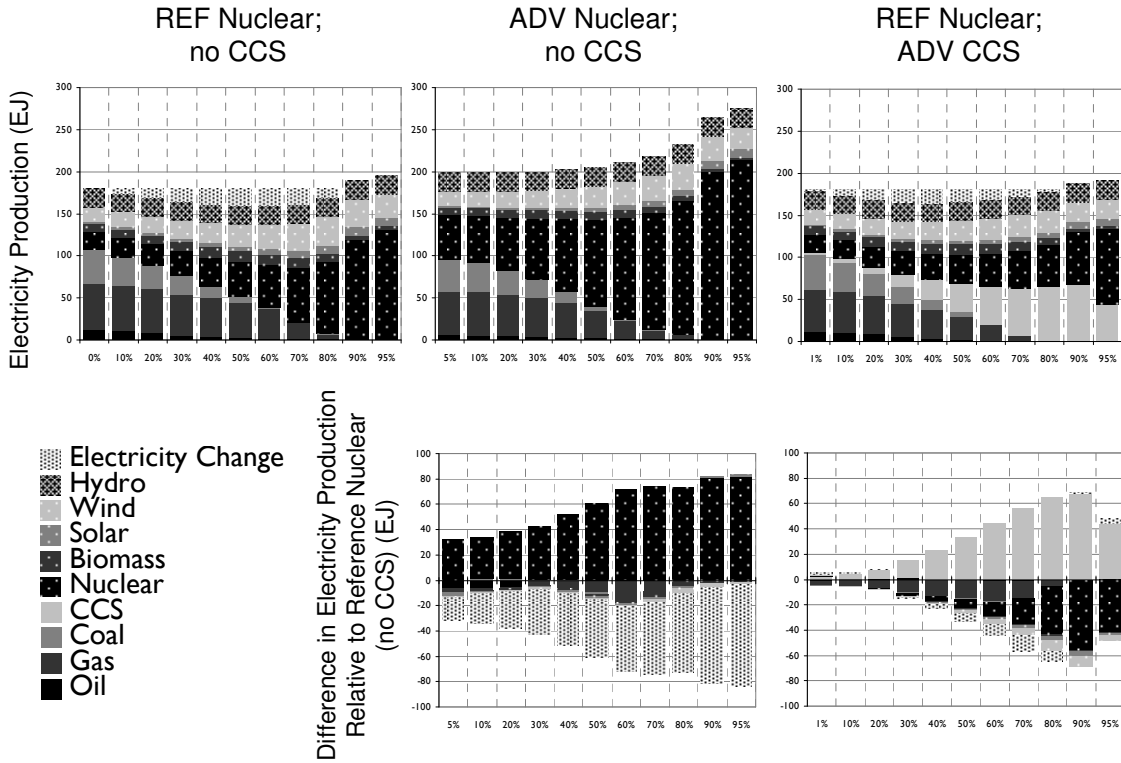
Figure 2.18: Electricity Production Technology Mix under Different Levels of Abatement

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In Figure 2.18, the top panels show the electricity production technology mix under each technology scenario and the bottom panels show the difference in electricity production by each technology compared to the reference scenario without CCS availability. The bottom panels clearly depict the differences among advanced nuclear and advanced CCS.

In the absence of a binding abatement constraint, advanced nuclear scenario already shows substantial increase in nuclear deployment. Nuclear power is a low-carbon technology that is already cost-competitive in many parts of the world. Substantially reducing the capital cost would make it even more competitive even without an abatement constraint. Advanced CCS scenario, on the other hand, shows little difference in the absence of a binding abatement constraint. CCS powerplant will always be more expensive than the same powerplant with capture component turned off, and thus little CCS technology will be deployed in the absence of a binding abatement constraint, no matter how low the cost is. This explains the difference in the initial abatement levels.

However, as the abatement level increases, the CCS becomes more and more competitive in the market, and starts to increasingly diverge from the reference MAC curve. A similar divergence of advanced nuclear MAC curve from the reference MAC curve is observed, but the *rate* at which this occurs is less than in the CCS case, especially at the high abatement levels.

Notice, in Figure 2.18, that the advanced CCS scenario shows rapidly increasing additional CCS deployment with respect to the abatement level (up to the point where CCS must be driven out due to a high carbon price). On the other hand, the advanced

nuclear scenario shows a rather slower *rate of increase*. In the absence of CCS

technology (and also in the absence of a low-cost energy storage technology for

intermittent sources), nuclear power may be the only technology capable of supplying the

majority of base-load electricity without substantially raising the electricity cost. As can

be seen in the reference scenario without CCS (top left panel in Figure 2.18), the

deployment of nuclear power increases rapidly to the point where more than half of

electricity is produced by nuclear power. Cost reduction in nuclear electricity

substantially increases nuclear deployment, but nuclear power still remains more or less

the sole means to decarbonize the remaining energy market. If rapid expansion in nuclear

hits an obstacle—such as uranium shortage, limits on uranium enrichment imposed due

to security concerns, limits on nuclear waste disposal capacity, etc.—there aren't any

other alternatives to substitute nuclear power at substantial scale at modest cost.

However, while CCS is a relatively expensive alternative, having CCS provides

an option to optimally diversify the base-load among nuclear and CCS. This allows the

energy market to avoid deploying either technology to the potential maximum, where the

marginal cost is likely to rapidly rise (due to unfavorable conditions). At high abatement

levels, this diversification option may prove to be valuable.

Combining the larger *initial abatement* of advanced nuclear and the faster *rate of
divergence* of advanced CCS inevitably results in a crossing point where the two

advanced MAC curves switch rankings (in this example, at around 30% abatement). The

exact level at which the crossing occurs is sensitive to the assumptions of the

technologies. The important insight from this example is that the relative values of the

two technologies are dependent upon the levels of abatement constraints imposed (or ultimately the level of damage from climate change).

Consider, for instance, a policy-maker facing a decision between the two advanced technologies that can be achieved with the same level of investment in R&D. If the abatement constraint—informed by the predicted level of climate damage—is lower than the crossing point, investing in advanced nuclear would be preferable; the MAC as well as the total abatement cost would be lower compared to the advanced CCS case. On the other hand, if the abatement constraint is higher than the crossing point, the investment decision could be different. Investing in CCS would yield a lower MAC than investing in nuclear, but the total abatement cost would not necessarily be lower for CCS. Only at the abatement level beyond the point[16] where the *integrated area* under advanced CCS MAC curve is smaller than that of advanced nuclear MAC curve, would CCS have advantage over advanced nuclear in terms of the total abatement cost.

The comparison between the advanced CCS and the advanced nuclear emphasizes the heterogeneities among characteristics of technologies. Not all technologies yield the same pattern of impacts on the MAC curve. Some technologies allow achieving some low levels of abatement solely induced by technological change at zero cost, but yield relatively smaller reductions in MAC at high abatement levels. Other technologies allow little zero-cost initial abatement, but yield substantially larger reductions in MAC at high abatement levels. The relative values of technologies depend on the level of abatement constraint. Under uncertainties regarding the potential level of damage from climate change, diversification of alternative energy technologies may be useful as a risk-hedging strategy.

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[16] Trivially, this point would be higher than the MAC curve crossing point.

2.5. Conclusion and Discussion

In this essay, I attempted to establish an analytical framework to assess the value of alternative energy-producing technologies under carbon dioxide emissions constraints. Particularly I focused on the impact that advanced technologies have on the marginal abatement cost. First, I developed a general framework defining marginal abatement cost and the conditions under which the energy production mix is optimized.

Second, I simplified the framework into a three technology model, and derived functions for marginal production, initial abatement, and the reductions in marginal abatement cost. It was observed that these three variables are determined by the magnitude of reduction in marginal cost of production, as well as the relative slopes of demand function and of marginal cost functions of competing technologies. I have found that, in general, larger benefit in terms of both initial abatement and reductions in MAC would occur when:

1. the reduction in the marginal cost of advanced alternative energy is larger;

2. the marginal cost of advanced alternative energy is less sensitive to quantity;

3. the marginal cost of conventional alternative energy is more sensitive to quantity;

4. the marginal benefit of aggregate energy is more sensitive to quantity.

Also, for initial abatement the slope of fossil technology's MC function matters: the less sensitive to quantity it is, the larger the initial abatement.

Third, I applied the framework to explain the differential behavior of the MAC curve in several simulated examples, each emphasizing different issues. First, I analyzed advanced solar PVs focusing on the confounding effect of deployment limitations. Second, I analyzed solar PVs focusing on the characteristics of competing technologies in

the market. Third, I analyzed CCS technologies focusing on the trade-off between cost

reduction and capture rate. Fourth, I analyzed a CCS technology and advanced nuclear

technology focusing on the different *distribution* of reduction throughout the MAC curve,

emphasizing the importance of diversification.

These examples show that depending on the technology specifications, the impact

of technological change on marginal abatement cost is not uniform across abatement

levels. Rather, different types of technological changes show distinct patterns of impact,

with relative strengths and weaknesses under different abatement levels. Merely focusing

on either aggregate marginal abatement cost or reduction in the cost of energy production

alone cannot adequately assess the value of technology under emission constraints. The

dynamic interactions in the market matter. It is important to look at the characteristics of

each technology to fully explain the interactions and resulting equilibrium.

The framework for assessing the impact of technological change on the abatement

cost developed in this essay is highly stylistic in its design. While the simplicity of the

design provides clarity to the issue, its drawback is limited coverage across

heterogeneous technological characteristics. For one thing, the framework exclusively

focuses on the cost aspect of the technologies; essentially reducing every other aspect of

the technologies into the cost curve. This is simple to do in an abstract model, but

numerically estimating the shadow cost of non-market barriers – most notably for nuclear,

with its regulatory constraints, security concerns, etc. – is a difficult task in practice.

Future research could explicitly address the non-market constraints and how innovation

in its broadest sense could impact the abatement cost by changing the stringency of such

constraints.

Another direction of potential extension is to explicitly address the interactions among multiple advanced technologies. This is the focus of Chapter 3. The current framework mainly addresses each technological change in isolation. However, as demonstrated in Chapter 3, the availability of competing advanced technologies in the market has large impact on the value of an advanced technology. The explicit focus on the substitutability of the technologies would provide a richer understanding of the issue.

The current framework is also deterministic in its design. It has limited focus on the deterministic process after the advanced technologies have been developed. However, both the advanced technology development process and the market interaction process of the technology are stochastic in their nature. Explicitly representing the stochastic nature could provide a broader picture of the process. Moreover, the current framework reduced future impact into a single aggregated variable, and it does not address the intertemporal dynamics of technology R&D. This simplification provides clarity to the deterministic process. However, with the introduction of stochasticity, explicit treatment of time dynamics would be necessary to adequately represent the resolution of the uncertainties. These two issues are the focal points of Chapter 4.

The framework developed in this essay is the first building block upon which the next two essays will be built. The potential extensions suggested here would further enrich the understanding of the impact of technological change on the abatement cost. The combined body of research would help inform public R&D investment strategies for energy technologies.

Chapter 3. Technology interactions among low-carbon energy technologies: What can we learn from a large number of scenarios?

3.1. Introduction

Stabilizing atmospheric concentrations of carbon dioxide (CO_2) at low levels will require a substantially different energy system from that of today. Improvements in the technologies that produce and consume energy will ease the transition toward a low-carbon energy system. Numerous near-term decisions related to this transition—for instance, choices about public R&D investments—are based on uncertain projections of the mix of different technologies that might be deployed to meet various stabilization goals. This uncertainty adds a layer of difficulty for decision makers attempting to define the appropriate focus of policies that might influence the development and deployment of technologies. Not only is there considerable uncertainty about the cost and performance of individual future technologies, there are also complex interactions among technologies. For instance, the benefits of improvements to nuclear power will depend on the degree of improvements in competing technologies such as solar photovoltaics or wind power. Given the numerous uncertainties involved, addressing such interactions has proved a demanding analytical challenge. This essay explores the implications of uncertain and interacting technological advances for the challenge of stabilizing CO_2 concentrations, through the use of a large number of runs of the Global Change Assessment Model (GCAM).[17]

Many studies have used simulation models to estimate the costs required to stabilize CO_2 concentrations contingent on combinations of assumptions about the cost

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[17] GCAM is a direct descendant of MiniCAM. The history of this family of models is discussed in more detail in Section 2.

and performance of potential low-carbon technologies (see, for example, Clarke et al., 2006, 2008; Luderer et al., 2009; Edenhofer et al., 2010; Richels et al., 2007). Such cost estimates can inform decisions about near-term abatement policies and about effective R&D investment strategies.[18] Given the large number of possible advances over a wide range of technologies that are relevant to climate change, most studies have relied on a representative scenario approach, in which a small number of scenarios are constructed to represent distinct combinations of advances.

Two recent efforts using MiniCAM, the predecessor of GCAM, illustrate both the strengths and the limitations of this approach. In the first of these, Baker et al. (2008c, 2009a, 2009b, 2010) used expert elicitation to estimate the probability of overcoming technological hurdles—such as cost, efficiency, and reliability—for several technology groups at different levels of R&D investment. These estimates were then combined with marginal abatement cost curves derived from MiniCAM to yield R&D priorities for the technologies. Several analyses were conducted, each focusing on a single group of technologies—solar photovoltaic (Baker et al., 2009a), carbon capture and storage, or CCS (Baker et al., 2009b), nuclear power (Baker et al., 2008c), and automobile battery (Baker et al., 2010)—while assuming that the use of all other technologies remained constant at business-as-usual levels. The interaction among the technologies, each with uncertain improvements, was thus left for future research.

In the second effort, analysis for the U.S. government's Climate Change Technology Program (CCTP) used a representative scenario analysis to evaluate the

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[18] A full-fledged portfolio approach to such R&D investments would require (1) defining the relationship between R&D investments and technological advance, (2) determining the implications or benefits of such advances, and (3) an analytical framework for combining these to evaluate and compare portfolios. This study focuses on the second of these three steps.

impact of advanced technologies and the interactions among them on the cost of abatement (Clarke et al., 2006, 2008). The CCTP scenarios were used to estimate the total cost of achieving different stabilization levels for a number of representative technology scenarios and to describe the associated energy system dynamics. Each representative scenario focused on a particular set of assumptions about successful technology development: some focused on successful development of individual technologies, such as advanced renewable energy, advanced end-use technology, advanced nuclear, or advanced CCS; others considered simultaneous advancement in combinations of these technologies. (Recent work in the RECIPE and ADAM model-comparison projects—Luderer et al., 2009; Edenhofer et al., 2010—used a comparable sensitivity-based approach to create representative scenarios.) Analyses such as these yield valuable insights about the interactions among technologies. For instance, they demonstrate that the cost reductions attributable to each advanced technology are not necessarily additive,[19] they provide a basis for comparing the relative value of particular technological advances, and they highlight the manner in which the underlying energy system might evolve differently under different technological futures.

Although the representative scenario studies provide valuable insights, questions remain regarding the degree to which a focus on only a small number of scenarios limits understanding of the full space of technological futures. To what degree might the representative scenario approach miss important insights or lead to erroneous conclusions that would be evident from more thorough exploration of the technological space? Or, put another way, to what degree does a full combinatorial approach corroborate the insights

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[19] That is, the sum of the stabilization cost reductions obtained from considering each advanced technology individually exceeds that obtained from considering such technologies in combination, because the technologies are (imperfect) substitutes for one another.

from the representative scenario approach, and what new insights does it provide? This essay will address these questions by comparing the CCTP representative scenarios with the results of a full combinatorial analysis of 768 model runs based on the CCTP technology assumptions.

Exploring large scenario sets and identifying key variables has a long history, particularly in combination with uncertainty techniques such as Monte Carlo analysis. For example, Reilly et al. (1987) performed uncertainty analysis of the IEA/ORAU model carbon emissions projection using the Monte Carlo method and analyzed the database of 400 samples. Scott et al. (1999) performed a similar exercise with the MiniCAM model. Gritsevskyi and Nakicenovic (2000) analyzed the effect of induced technological learning and uncertainty on future energy systems by examining 130,000 scenarios with 520 alternative technology dynamics. Webster et al. (2008) conducted a 400-sample Monte Carlo simulation study using in-house expert elicitation on technologies and social parameters of the EPPA model, and they analyzed the relative contribution of uncertainty in the parameters considered.

This essay builds on both of these traditions. I apply variation in technology assumptions from the CCTP scenarios to build a database of 768 scenarios. In contrast to explicit uncertainty-based studies using probabilistic sampling techniques, this dataset is constructed on a full combinatorial approach, and the focus of the resulting analysis is on exploration of the technological space. This analysis is the first part of a larger exploratory modeling project. In this part of a typical exploratory modeling project, an experimental design consisting of a carefully chosen set of different combinations of uncertain model input parameters is first created and analyzed through a simulation

model. In the second part, the resulting database is analyzed through a combination of interactive visualization, statistical analysis, and computer search in order to identify and test alternative hypotheses relevant to some decision problem (Bankes, 1993). A primary focus of the project is to explore the market interactions among advanced technologies and their combined impact on the stabilization cost.

After introducing the modeling tool used in this study (GCAM) in Section 3.2 and describing the experimental design in Section 3.3, in Section 3.4 I summarize the database of technology combinations and corresponding stabilization costs from three different perspectives, each addressing different policy questions. The first approach is a broad assessment of the degree of variation in energy consumption and stabilization costs across all scenarios in the dataset, to highlight some general characteristics of the technology space. The second approach is an assessment of the ranges of stabilization costs associated with each level of technology development, which might be useful if the policy goal is to maintain costs below a particular level. The third approach is an assessment of the stabilization cost *reduction* associated with improvements in individual technologies, which might be useful if the goal is to allocate R&D budgets among technologies using a standard portfolio-based approach.

Last section concludes with summary thoughts on the analysis and examines what has been learned beyond what representative scenario analysis has revealed. This section also briefly introduces an example of the dataset utilization in a formal scenario discovery method, performed to identify the combinations of technology assumptions most strongly associated with an inability to meet stabilization targets at an acceptable cost.

3.2. The Global Change Assessment Model

The analysis in this essay uses the GCAM integrated assessment model. GCAM was built on the foundations of MiniCAM (Edmonds et al., 2004; Kim et al., 2006; Clarke et al., 2007; Brenkert et al., 2003), which, in turn, was a descendant of a model developed by Edmonds and Reilly (1985). GCAM and its predecessors have been used extensively in global climate change analyses conducted for the Intergovernmental Panel on Climate Change (IPCC), various national governments, and nongovernmental organizations.[20]

GCAM links a global energy economy model and an agricultural land-use model with a suite of coupled gas-cycle, climate, and ice-melt models integrated in the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC).[21] GCAM tracks emissions and concentrations of greenhouse gases and short-lived chemical species.[22] The economic simulation of GCAM is driven by assumptions about population size and labor productivity that determine potential gross domestic product in each of 14 geopolitical regions. GCAM is solved by establishing market-clearing prices for all energy, agriculture, and land markets such that supplies and demands for all markets balance simultaneously; that is, there are no excess supplies or demands for land, agricultural products, primary energy, final energy, or energy services.

GCAM is solved in 15-year time steps through 2095. It is a dynamic-recursive model: decisions in any period are made only with information about that period, but the

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[20] The model description can be found at www.globalchange.umd.edu/models/gcam/.
[21] For this study MAGICC 4.1 (Wigley, 2003) was used.
[22] Fifteen greenhouse-related gases are tracked: CO_2, CH_4, N_2O, NO_x, VOCs, CO, SO_2, carbonaceous aerosols, HFCs, PFCs, and SF_6. Each is associated with multiple human activities that are explicitly modeled in GCAM. All greenhouse gases are priced in U.S. dollars per ton of CO_2 equivalent according to their 100-year global warming potential, to ensure balance of the climate policies, but given my focus on energy technologies, in this essay I analyze only the emissions and the cost of abatement of CO_2.

consequences of decisions made in one period (resource depletion, capital stock build-up, etc.) sequentially influence subsequent periods, including the decision set available in those periods.

The GCAM energy system includes representations of primary energy resources, the processes involved in primary energy production and transformation to final fuels, and the employment of final energy forms to deliver energy services. Energy supplied from depletable resources—fossil fuels and uranium—depends on the abundance and grade of available resources as well as available extraction technologies. These depletable resources exhibit increasing costs in the absence of significant technical change. As the more attractive resources are consumed, less attractive resources are exploited, and, all else being equal, costs rise. Renewable resources such as wind and solar are produced from graded renewable resource bases.

Primary energy forms include oil, natural gas, coal, bioenergy, uranium, hydropower, geothermal, solar, and wind energy. GCAM models the transformations from these primary energy forms into the following six final energy forms: refined liquids, refined gas, coal, commercial solid bioenergy, hydrogen, and electricity. These energy forms are then used to provide end-use services in the buildings, industry, and transportation sectors.

GCAM is a technology-rich integrated assessment model. It contains detailed representations of technology options in all of the economic components of the system. Technology choice in GCAM is determined by market competition. Individual technologies compete for market share based on their technological characteristics (their efficiency in producing energy from inputs), the cost of inputs, and the price of outputs.

GCAM uses a logit choice methodology to determine the market shares of different fuels and technologies, based on a probabilistic model of the relative prices of the competing fuels or technologies (Clarke and Edmonds, 1993; McFadden, 1974, 1981). This methodology is based on the idea that every market includes a range of different suppliers and purchasers, each of which may have different needs and may experience different local prices. Therefore, not all purchasers will choose the same technology when the average price of that technology is lower than the average price of a competing technology. The logit choice methodology allocates market shares based on prices, but ensures that higher-priced goods gain some share of the market, which is consistent with the heterogeneity observed in real markets.

The future rates of change in the characteristics of technologies for producing, transforming, and utilizing energy under different technology scenarios are explained in detail in the following section. All other model assumptions in this analysis are based on the version of the model used in the 2008 CCTP study (Clarke et al., 2008).

To meet particular atmospheric CO_2 concentration goals, emissions trajectories are imposed on the model. These pathways ensure that the CO_2 concentration does not exceed the stabilization target at any point in the modeling timeframe (Fig. 3.1). The stabilization costs for each model period are estimated by integrating the area under the marginal abatement cost curve.[23] The net present value of the total cost of stabilization is

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[23] There are many metrics used to quantify the economic implications of mitigation. Standard cost metrics include GDP loss, consumption loss, the area under the marginal abatement cost curve, and compensated variation and equivalent variation of consumer welfare loss. The area under the marginal abatement cost curve used here represents the total abatement costs of the stabilization policy, including reductions in both consumer and producer surplus (Calvin et al., 2009) but excluding surplus gains through avoided climate damages. This metric is appropriate for a partial equilibrium model like GCAM, where sectors less related to emissions are represented in a highly abstract manner.

calculated by summing the discounted annual costs of stabilization from 2005 to 2095. A real discount rate of 5% per year is used for discounting future periods.
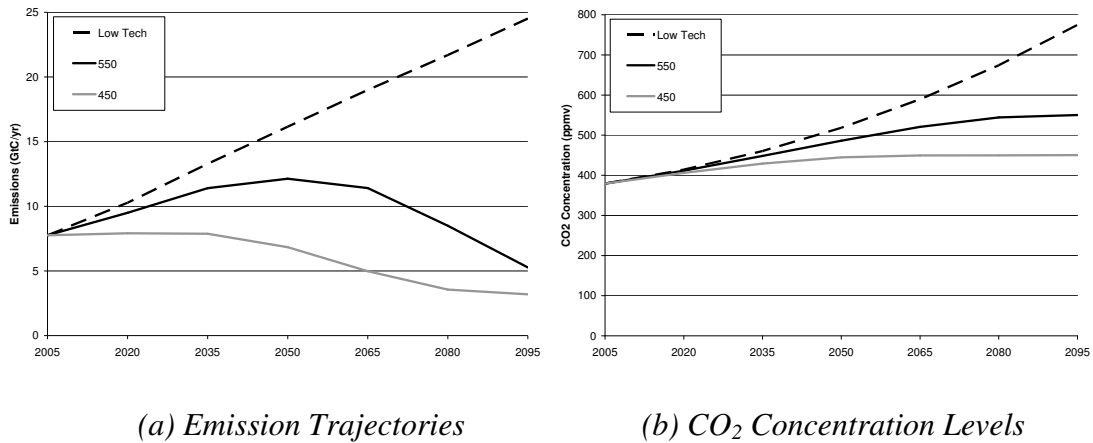
| *(a) Emission Trajectories* | *(b) CO₂ Concentration Levels* |

Fig. 3.1. Representative trajectories for atmospheric CO2 stabilization at 450 ppmv and 550 ppmv. Maximal unconstrained CO_2 trajectories ("Low Tech") are shown for comparison, represented by the most technology-poor combination (no new nuclear, no CCS, and reference level for all other technologies).

3.3. Experimental Design

3.3.1. Background: The CCTP Scenarios

Because the research in this study is built from a previous set of representative scenarios (the CCTP scenarios; Clarke et al., 2008), it will be helpful to first review this set of scenarios. The CCTP scenarios explored 10 distinct technology combinations based on variations in assumptions regarding both supply and end-use technologies (Table 3.1). They included both a fully advanced scenario, in which all technology assumptions were set at their most optimistic levels, and a "reference" scenario, in which all assumptions were set to their more pessimistic, or reference, levels. Eight additional combinations of

both advanced and reference assumptions were then constructed to create a set of scenarios that lie between the above extremes. These intermediate scenarios are intended to provide insight into particular technological combinations that might prove particularly important. Of course, these 10 scenarios are not a full representation of all the technology futures that might evolve based on the underlying technology assumption sets.

Table 3.1. Technology combinations used in the CCTP scenarios.

	Reference	Nuclear Reference	Nuclear Advanced	CCS	Bio and CCS	Renewables	End Use	End Use & Renewables	Hydrogen and Supply	Advanced
	Ref	Nuc Ref	Nuc Adv	CCS	Bio CCS	RE	EE	EERE	Supply	Adv
TRN: Electric Vehicles	REF	REF	REF	REF	REF	REF	ADV	ADV	REF	ADV
TRN: Fuel Cell Vehicles	REF	REF	REF	REF	REF	REF	ADV	ADV	ADV	ADV
TRN: Other	REF	REF	REF	REF	REF	REF	ADV	ADV	REF	ADV
Buildings	REF	REF	REF	REF	REF	REF	ADV	ADV	REF	ADV
Industry	REF	REF	REF	REF	REF	REF	ADV	ADV	REF	ADV
Electricity and H$_2$ CCS	FIX	FIX	FIX	REF	REF	FIX	FIX	FIX	REF	REF
Dedicated Energy Crops	REF	REF	REF	REF	ADV	ADV	REF	ADV	ADV	ADV
Hydrogen Production	REF	REF	REF	REF	REF	REF	REF	REF	ADV	ADV
Wind Power	REF	REF	REF	REF	REF	ADV	REF	ADV	ADV	ADV
Solar Power	REF	REF	REF	REF	REF	ADV	REF	ADV	ADV	ADV
Nuclear Fission	FIX	REF	ADV	FIX	FIX	FIX	FIX	FIX	ADV	ADV
Geothermal	REF	REF	REF	REF	REF	ADV	REF	ADV	ADV	ADV

Note: TRN, transportation; CCS, carbon capture and storage.

Source: Modified from Clarke et al. (2008).

Table 3.2. Levels of technologies considered in this study.

		Fixed	Reference	Advanced
Supply Technology	**Solar**	N/A	Capital costs drop by 1%-2% per year 2005-2050	Capital costs drop by 2%-3.5% per year 2005-2050
	Wind	N/A	Capital costs drop by 0.25% per year 2005-2050	Capital costs drop by 0.5% per year 2005-2050
	CCS	No CCS in any applications	CCS available in electricity, hydrogen, and cement sectors (starting at about $40 / t CO2)	N/A
	Nuclear	Nuclear power generation fixed at 2005 levels	Nuclear power available at $2300/kW in 2020, decreasing at 0.1% per year	Nuclear power available at $2300/kW in 2020, decreasing at 0.3% per year
End-Use Technology	**Buildings**	N/A	Improvement in building technologies and shells based on EIA (2007)	Accelerated improvement in costs and performance of energy-saving technologies and building shells
	Transport-ation	N/A	Improvement in transportation technologies based on EIA (2007)	Accelerated improvements in conventional technologies, and availability of low-cost electric and fuel-cell light duty vehicles
	Industry	N/A	Technology efficiencies improve at 0.1% per year; process intensities improve at 0.35% per year	Boiler and motor system efficiencies improve by 10% and 25% by 2035; best available practices from IEA (2007) are in use by 2035
Other	**Other**	N/A	Long-term agricultural productivity improvement: 0.25% per year. Engineered geothermal systems (EGS) not available.	Long-term agricultural productivity: 0.5% per year. Accelerated improvements in hydrogen production. EGS available

Source: Modified from Clarke et al. (2008).

3.3.2. A Full Combinatorial Approach

To create the database of simulation runs, 384 combinations of assumptions about the future cost and performance of eight different advanced low-carbon technologies were developed, as shown in Table 3.2. Assumptions about each individual technology—three levels of cost and performance for nuclear, and two levels each for solar, wind, CCS, buildings, transportation, industry, and a group of "other" technologies—were adopted from the CCTP study (Clarke et al., 2008). A full combinatorial design over these technology levels gives the 384 cases ($3 \cdot 2^7 = 384$).

Stabilization costs, primary energy consumption, and other key outputs were then calculated using GCAM for each of 768 cases: each of the 384 combinations of technology assumptions combined with each of two CO_2 stabilization levels: 450 ppmv and 550 ppmv. The implications of these low stabilization targets are of significant concern for policy makers.

Table 3.2 describes the differences between the sets of assumptions for each level for each technology. Reference-level technology pathways do not represent static technology; rather, they represent improvements in the technologies at a level that can be considered as a point of departure for the exploration of more aggressive levels of advance. Advanced-level technology pathways represent accelerated improvements in the technologies that typically result in lower cost per energy output for low-carbon supply technologies and lower energy intensity (or higher autonomous energy efficiency improvement—AEEI) for end-use technologies. Although all assumptions about future technology are inherently speculative, the advanced levels are designed to be considered plausibly achievable with sufficient investment to overcome the technical hurdles.

Fixed technology pathways represent special cases where the technologies are artificially fixed in their base year (2005) quantities and do not freely compete in the market. For CCS, this represents a future in which society does not utilize the technology at all because of concerns regarding sustainability or reliability or for any currently unknown reason. For nuclear energy, it represents a future in which nuclear electricity production is held constant at its 2005 level. Such a future may be possible given concerns regarding proliferation, waste storage, or safety.

Finally, a generic group of technologies is lumped together as "others," also with a reference and an advanced level. Technologies that are included in the model but were excluded from individual analysis, such as hydrogen, geothermal, and agricultural technologies, are included in this group.

3.4. Results

This section summarizes the database of 768 scenarios using the three approaches described above, each addressing different policy questions, and describes the relevant findings.

3.4.1. Range of Outcomes

Fig. 3.2 shows a full scatterplot of results from the 768 scenarios. Cumulative primary energy consumption from 2005 through 2095 is shown on the horizontal axis and the net present value of stabilization costs on the vertical axis. The plot demonstrates the trade-offs between energy consumption and costs over the technology combinations

explored in the study. Here I highlight several elements of the scenarios that are evident from this overview.
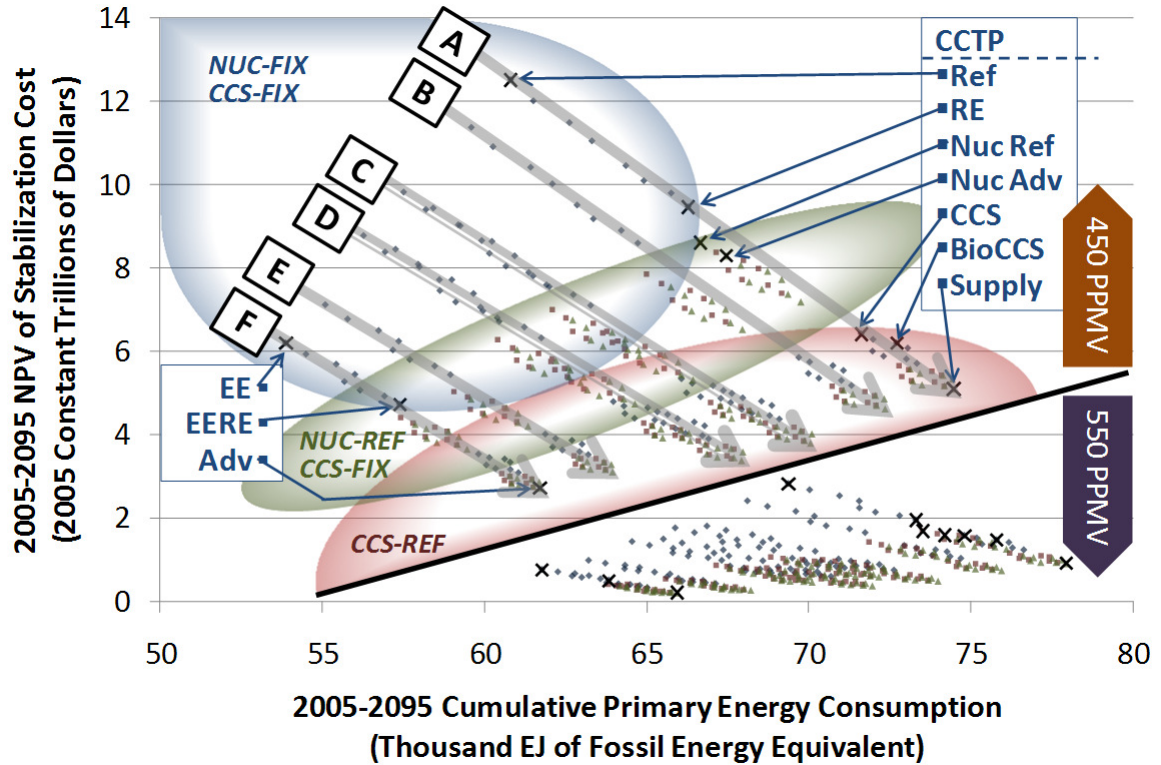
Fig. 3.2. Scatterplot of simulation output. Diagonal clusters are formed by combinations of common end-use technology levels (transportation, buildings, and industry). Clusters C and D are in fact overlaps of two separate clusters each. The cost reduction potentials of advanced building and transport technology are very similar at the 450-ppmv stabilization level. CCTP scenarios marked for reference. Technology levels associated with each cluster are as follows:

A, TRN-REF, BLD-REF, IND-REF;
B, TRN-REF, BLD-REF, IND-ADV;
C, TRN-REF, BLD-ADV, IND-REF or TRN-ADV, BLD-REF, IND-REF;
D, TRN-REF, BLD-ADV, IND-ADV or TRN-ADV, BLD-REF, IND-ADV;
E, TRN-ADV, BLD-ADV, IND-REF;
F, TRN-ADV, BLD-ADV, IND-ADV.

As would be expected, costs are higher for the 450-ppmv scenarios than for the

550-ppmv scenarios, and, in general, energy consumption is lower in the 450-ppmv

scenarios. There is significant overlap in energy consumption, but only limited overlap in

costs. Only the most expensive cases of the 550-ppmv scenarios are comparable in costs to the least expensive cases of the 450-ppmv scenarios.

There is distinct diagonal clustering of the scenarios, largely driven by discrete end-use efficiency combinations. A shift from one diagonal cluster to another represents an end-use technology-induced conservation, where more efficient end-use technology allows lower energy consumption and lower stabilization cost. On the other hand, the variance within a diagonal cluster represents supply technology-induced price reduction, where low-cost, low-carbon technologies reduce the market price of energy at a given emissions constraint. This reduction in energy price, in turn, reduces the stabilization cost and increases energy consumption.

Wide variation in stabilization costs is observed, reinforcing the notion that technology is a significant factor in determining these costs. For example, for a 450-ppmv target, the worst-case scenario with fixed nuclear, no CCS, and all other technologies at the reference levels has the highest stabilization cost, at $13 trillion, whereas the best-case scenario with reference level CCS and all other technologies at the advanced levels has the lowest, at $2.7 trillion. The absolute magnitude of the range of costs is much larger for the 450-ppmv target: about $9.8 trillion, compared with $2.6 trillion for the 550-ppmv target.[24] Under more stringent targets, the significance of advanced technologies becomes more pronounced.

One goal of this study is to compare the results of the full combinatorial approach used here with a representative scenario approach. To highlight this comparison, I have mapped the 10 CCTP 450-ppmv scenarios (Clarke et al., 2008) over the scatterplot. By

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[24] In relative terms, the stabilization cost range is wider for the 550-ppmv than for the 450-ppmv target. The minimum cost is 93% below the maximum cost for the 550-ppmv scenarios, and 78% below the maximum cost for the 450-ppmv scenarios.

design, the CCTP scenarios are selected to represent the extremes and several other key data points. These representative scenarios thus *span* the technology space, covering all four corners. Indeed, one of the reasons that the CCTP scenarios can provide useful insights despite their small number is that they are carefully designed to provide a sense of the extremes. In contrast, the full combinatorial set is designed to fully *represent* the space, revealing the interior distribution.

Note that all CCTP scenarios lie within the two outside diagonal clusters: all end-use technologies at their reference level (cluster A) or all at their advanced level (cluster F). Understanding the cases in the regions largely ignored by the representative scenario analysis is one of the potential benefits of a full combinatorial approach. The pertinent comparison in this regard is whether additional insights are available by exploring the full space rather than simply the extremes.

3.4.2. Range of Stabilization Costs by Technology

Fig. 3.3 shows histograms of stabilization costs from the same scenarios for two technologies: CCS (left panel) and buildings technology (right panel); each panel shows two histograms, each representing a subset of scenarios associated with a specific level of the indicated technology. Separating out the distributions by the level of development in one specific technology provides insights into the role of each of these different technological improvements. Perhaps the most salient point is that merely allowing CCS to compete in the market reduces total stabilization costs roughly by half in the high cost scenarios. Furthermore, the clustering of costs is tighter with CCS than without CCS. To a large degree, the presence of CCS serves as a hedging strategy by truncating the high-

cost tail. Costs in the low-cost range are less affected by the presence or absence of a

particular technology such as CCS than costs at the high end of the range. The presence

of CCS is most valuable when substitutes such as nuclear power are not available. In

contrast, improvements in buildings technologies result in a relatively constant shift,

consistent with the nature of advanced end-use technologies that allow given end-use

service to be provided with less energy by increasing efficiency (discussed in more detail

later in this section).

(a) CCS focus   *(b) Buildings focus*
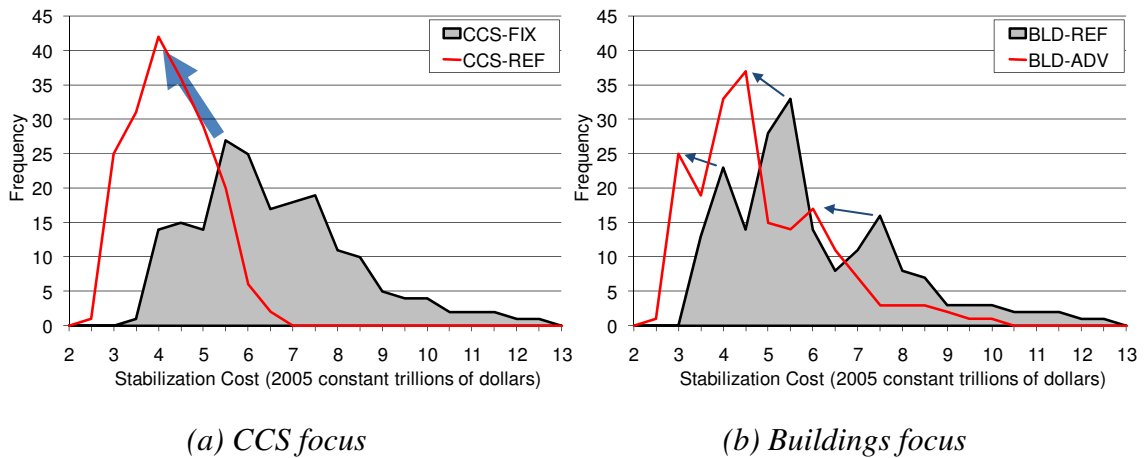
Fig. 3.3. Distribution of the cost of CO2 stabilization at 450 ppmv under different technology levels. CCS-FIX, CCS technology fixed in base year (2005); CCS-REF, CCS technology set at reference level (see Table 3.2); BLD-REF, buildings technology set at reference level; BLD-ADV, buildings technology set at advanced level.

Fig. 3.4 shows the range of stabilization cost estimates associated with each

specific level of each individual technology. For example, the first column on the left in

each panel shows costs for all 192 scenarios with reference-level solar technology, and

the next column shows the other 192 scenarios with advanced-level solar technology.

Together these two columns represent the full set of scenarios constructed for the

indicated stabilization level. Each column is an abstract representation of the histogram in

Fig. 3.3, where each horizontal bar represents an incidence of a stabilization cost level

under a specific technology combination. For example, the last column in the top panel of Fig. 3.4 represents the same distribution as the partial histogram labeled CCS-REF in the left panel of Fig. 3.3.

In Fig. 3.4 what may appear to be solid black boxes are overlapping incidences equivalent to the modal points in a histogram, whereas the sparsely populated areas correspond to the troughs in a histogram. The minimum and maximum cost estimates are shown with longer bars for emphasis. These correspond to the situations in which all other technologies are at their most advanced or their least advanced level, respectively. The gray boxes show the range for the middle half of all the considered cases.

Exploring the distribution of total costs associated with individual technologies provides insights that might be of value in a risk-management approach to portfolio planning. If the policy goal is to ensure that stabilization costs do not exceed a particular level, then it is useful to know which single technological advance would deterministically achieve this goal. (The scenario discovery methods performed in McJeon et al. (2011) explore this same question, but using formal cluster-finding algorithms that allow for more nuanced understanding and greater insight into multiple technology interactions.) It is evident from Fig. 3.4 that some technologies substantially reduce the number of ways that stabilization costs might exceed a specified level.

Consider worst-case scenarios where all other technologies have failed to advance. The long horizontal bars at the top of each column in Fig. 3.4 represent these cases. For example, if CCS technology were fully available in the market (CCS-REF), then even if all others failed to advance, the stabilization cost would not exceed $6.5 trillion for 450 ppmv and $1.6 trillion for 550 ppmv.

450 ppmv
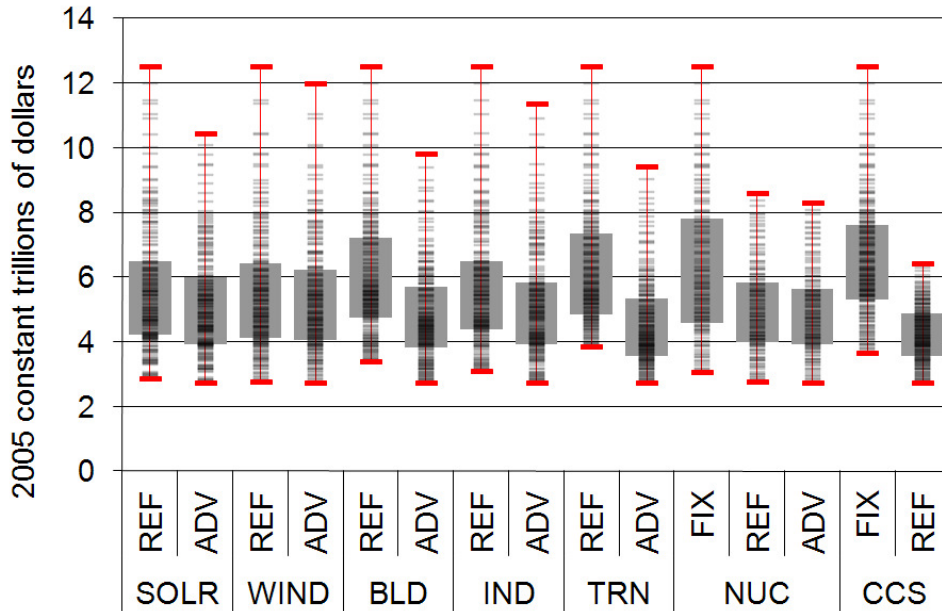
550 ppmv
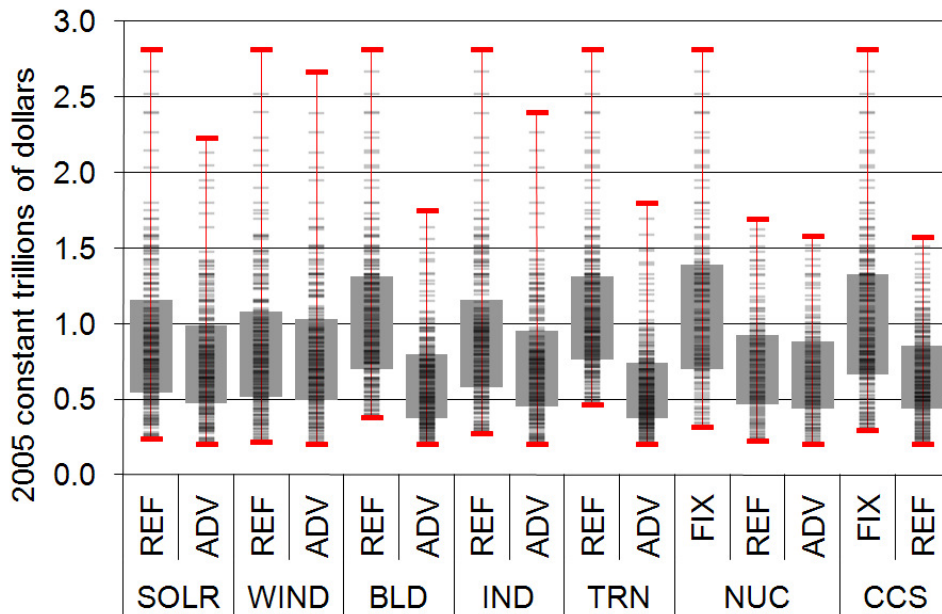
Fig. 3.4. Distributions of stabilization cost for each technology level. Thick horizontal bars at extremes of each column indicate minimum and maximum stabilization costs; all other incidences of stabilization costs are marked with thin bars; gray boxes indicate the middle half of considered cases. REF, reference; ADV, advanced; SOLR, solar; BLD, buildings; IND, industry; TRN, transportation; NUC, nuclear; CCS, carbon capture and storage.

If CCS were not available, however (CCS-FIX), the costs could be more than $12 trillion and $2.8 trillion, respectively. One can imagine an implicit constraint on the maximum stabilization cost, beyond which the cost would be socially unacceptable. Having a particular advanced technology or a combination of technologies available would guarantee that the constraint would be met. Investing in these technologies may serve as a hedging strategy against the potential failure of other technologies.

A more general way to understand the risk-management characteristics is to observe the degree to which individual technological advances *compress* the distribution of stabilization costs. For example, Fig. 3.3 showed that the inclusion of CCS compressed the cost distribution by eliminating many of the outcomes with the highest stabilization cost, but had a more modest influence on those with low stabilization cost; technological advances in the buildings sector *shifted* the distribution in a more consistent manner. Put another way, the inclusion of CCS had a larger effect on the high-stabilization-cost outcomes (pessimistic technology combinations) relative to the low-stabilization-cost outcomes (optimistic technology combinations) than did the technological advances in the buildings sector.

Generally speaking, the supply technologies—particularly nuclear and CCS— tend to be more effective at limiting stabilization costs in the worst-case technology scenarios than the end-use technologies. So long as the end-use sectors can largely be supplied by electricity produced from the advanced supply technologies, advances in these technologies can bring down the stabilization cost across the economy. In contrast, advances in end-use technologies are largely contained within their sector; for example,

no matter how effective building insulation materials become, they cannot reduce emissions in the transportation sector.

On the other hand, improvements to end-use technologies tend to have a larger relative effect on costs in the best-case scenarios than the supply technologies. The best case—the thick horizontal bar at the bottom of each column—represents the situation where every other technology succeeds. When there are multiple low-carbon supply technologies available, the presence of an additional low-carbon supply technology yields little benefit; there is a substantial degree of substitution between these technologies. The end-use technologies do not exhibit this substitution effect for two reasons, the first by nature and the second by design. First, the logic of sectoral separation applies here as well; end-use technologies influence a distinct portion of the energy system, regardless of advancement in other sectors. Second, the end-use sectors in this study are represented as *aggregate* sectors, unlike the supply technologies, which are represented individually. If a more disaggregated approach to end uses were used in this analysis, one in which intrasector technology competition was explicitly introduced—such as a competition between electric vehicles and hydrogen vehicles—many end-use technologies might behave more like the supply technologies.

Note that this analysis does not make any assumptions about the probabilistic weighting of the 768 cases. Rather, it is intended to help demonstrate key patterns in the interactions among technologies. For instance, the notion that some technologies can maintain stabilization costs below some specified level is true no matter what the probabilistic weighting of the technological advances. Having demonstrated such patterns, the analysis presented in this essay can help inform the latter stages of a full decision

analysis, in which decision makers might wish to place probability distributions over these cases to help suggest which policies they wish to pursue.

Without attaching such probabilities, interpreting the middle of the distribution in definitive terms is more difficult than interpreting the extreme values. For instance, the gray boxes that represent the middle half of the cases considered should not be taken as the middle 50% probability range, but rather as the range where many of the scenarios are congregated. In terms of general patterns, the gray boxes give some indication of the relative compactness of the distributions of stabilization costs. Only in cases where the majority of other technologies fail would the stabilization cost be above the box. Conversely, except in a few fortunate cases where most other technologies succeed, the stabilization cost would be above the bottom of the box. The boxes tend to be more compact for end-use technologies, especially under less stringent stabilization targets.

3.4.3. The Magnitude of Stabilization Cost Reduction: The "Value" of Technology

Fig. 3.5 shows the range of *reductions* in stabilization cost associated with successful advancement of each technology. The charts are designed in similar fashion to those in Fig. 3.4. For example, in the top panel, the thick horizontal bar at the bottom of the CCS column represents the cost difference for stabilization at 450 ppmv between CCS-FIX and CCS-REF when all other technologies are at advanced levels (that is, the difference in level between the bottom thick bars in the CCS-FIX and the CCS-REF columns in the top panel of Fig. 3.4). In a sense, each data point here represents a possible "value" of technological change. In contrast to the information on total stabilization costs, these data would be most useful for developing an R&D investment

portfolio under a budget constraint in which the goal is to obtain the maximum total reduction in stabilization cost.[25]

Note that two distinct technological changes in the nuclear technology are represented. The first one, nuclear-A represents the change from NUC-FIX to NUC-REF: a removal of quantity constraint on nuclear deployment without any change in the cost of nuclear power. The second one, nuclear-B represents the change from NUC-REF to NUC-ADV: a reduction in the capital cost of nuclear power

Several observations are worth noting, most of which reiterate the themes from Section 3.4.2. First, there are vast differences among technological advances in terms of their impacts on stabilization cost. For example, advances embodied in wind, nuclear-B, and solar have smaller impacts than those represented by CCS and nuclear-A. One reason that some technological advances have a lower value than others is that there are limitations on the maximum deployment of the associated technologies. For example, the value of advances in solar in these scenarios is limited by the assumption that the intermittency of solar power limits the total share of solar power that could be incorporated into the electric grid. If the scenarios had included more aggressive assumptions about the ability to incorporate solar power—for example, through electric storage technologies or grid management—the benefits could have been higher (Baker et al., 2009a). Wind is subject to similar limitations.

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[25] Combined with probabilities of success, which would be associated with specific levels of R&D investments in a formal portfolio analysis, the reduction potential of stabilization costs can show which technologies' *expected returns* on investment are consistently high given the probabilities of success of other technologies.

450 ppmv

550 ppmv
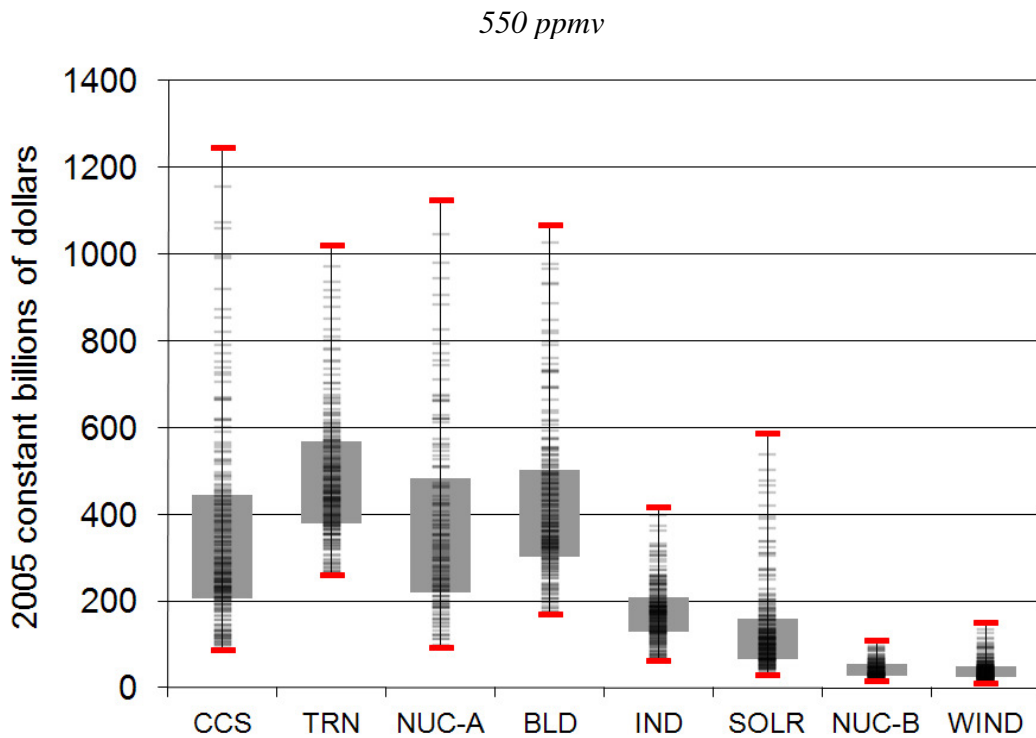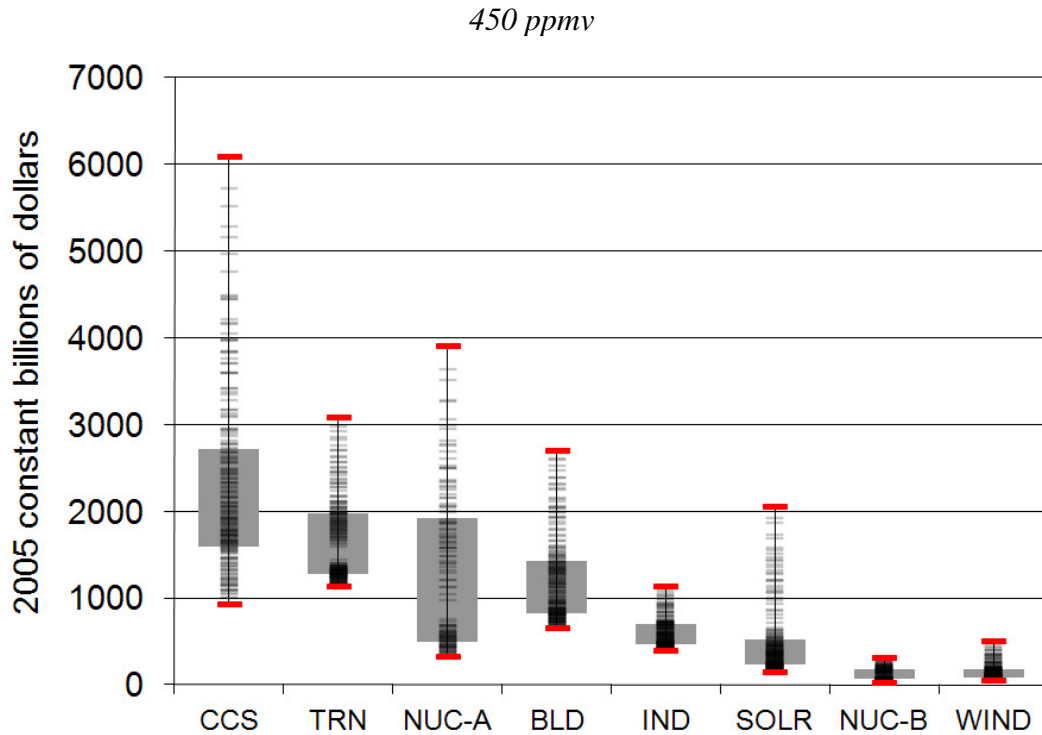
Fig. 3.5. *Distributions of reduction in stabilization cost.* Thick horizontal bars at extremes of each column represent cases where all other technologies have their worst (top) and their best (bottom) possible future performance. NUC-A, advancing from NUC-FIX to NUC-REF; NUC-B, advancing from NUC-REF to NUC-ADV.

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In other cases, the benefits of an advance are limited because it has minimal effect on the scale of deployment and mainly reduces the cost of a fixed amount of deployment. The two options for improvements in nuclear provide an interesting example of this. Reducing nuclear capital costs (nuclear-B) provides less stabilization cost reduction than removing quantity constraints on nuclear deployment (nuclear-A), which would result from advances in technologies (or social institutions) associated with nonmarket issues such as waste disposal, proliferation, or safety. At its reference capital cost, nuclear is already cost-competitive and saturates much of its potential market. The bottleneck exists in nonmarket issues. Reducing the cost of power plants, most of which would already be built at the reference cost, provides less value than developing technologies that will allow widespread deployment in the first place.

A comparison of the values of technological advances in wind and CCS provides another window into this dynamic. The benefits of improvements to wind technology costs are limited not only by constraints on wind deployment, but also by the forecast that future wind technology is likely to be already competitive in many markets at reference costs. In contrast, the technological advance in CCS explored in this study is limited to making CCS available, which itself has extraordinary value. Advances that further reduce the costs of CCS would not have nearly as much value as the advances that allow the technology to be used in the market, at reference costs (Baker et al., 2009b).

Some technological advances deliver substantial benefits even in a technology-rich future, whereas the impact of others is near zero. For example, improving nuclear capital costs (nuclear-B) provides little benefit when all other advanced technologies are

available. On the other hand, advanced transportation technologies provide significant benefits in the same setting.

It should be noted that a small impact on stabilization cost should not be interpreted as a small value in terms of *R&D investment* strategy. It may well be the case that small-impact technologies also require small investment. For instance, expert elicitation results by Baker et al. (2008c) show that the investment required for some advanced nuclear technologies is more than an order of magnitude higher than that required for the advanced solar technologies considered in Baker et al. (2009a).

Second, the ranges of benefits across the full suite of technology combinations differ substantially among technologies. These ranges show that technologies are not always utilized to their full potential. Some have relatively narrower ranges (or consistent values; e.g., transportation), whereas others have relatively wide ranges (or diverse values; e.g., nuclear). These differences are consistently present for both the full range and the middle range represented by the gray boxes in Figs. 3.4 and 3.5.

More generally, supply technologies exhibit wider ranges than end-use technologies. The reasoning follows the same line of logic as in Section 3.4.2. Among the technologies considered, supply-side technologies are highly substitutable; when several advanced inexpensive electricity technologies are available, having another yields decreasing incremental benefits. On the other hand, when there are no other advanced technologies in the market, the first advanced technology is highly valuable and will penetrate the market to the maximum extent possible. However, representing each end-use sector as a separate and aggregate sector puts limitations on this substitution effect in the results. Disaggregation of the end-use sectors would partially introduce the

substitution effect, resulting in larger ranges of stabilization cost reduction potential, albeit confined to inherent sectoral limitations.

Third, there are differences in the patterns between the 450-ppmv and the 550-ppmv stabilization limits. Overall, both the range of stabilization cost reductions and the absolute value of the reductions are substantially diminished in the 550-ppmv case (note the scale difference in Fig, 3.5). The relaxed stabilization target reduces the total stabilization cost, and hence there is less reduction potential to begin with. So, although the relative range may have widened, the absolute range has been reduced.

In addition, there is a switch in rankings between nuclear-A (removing quantity constraints) and CCS when moving between the two stabilization levels. CCS has a larger impact at the 450-ppmv level in terms of maximum, minimum, and the gray box, whereas nuclear-A has a larger impact at the 550-ppmv level under all measures except for the maximum. One reason for this is that removing nuclear energy constraints yields benefits even if there is minimal constraint on carbon emissions, whereas CCS is valuable only in the presence of a sufficient carbon constraint. This dynamic persists more strongly in the less stringent 550-ppmv scenarios than in the more stringent 450-ppmv scenarios.

A second reason is that although both technologies are increasingly valuable with a tightening of carbon constraints, the rate of increase is faster for CCS technology. This effect is driven by the assumption that the currently observed aversion to nuclear power persists throughout the modeling period. In contrast, the observed preferences toward fossil power plants are assumed to carry over to fossil CCS plants in the future.

A more general way to think about these dynamics is that the lower-unit-cost technology with limited social acceptance potential—in this case, nuclear—gets deployed

at the lower abatement level and hence yields relatively consistent values even under the less stringent stabilization levels. On the other hand, the abundant high-cost technology, CCS, gets deployed only as other options are exhausted. Hence, obtaining a high value for CCS requires a combination of poor technology availability and stringent targets.

The value of end-use technology improvements relative to that of supply technology improvements is higher at the 550-ppmv stabilization level than at the 450-ppmv level. One reason is that many of the technological advances in end-use sectors are associated strictly with improvements in efficiency. The same degree of efficiency improvement, which allows end-use services—heating, cooling, lighting, etc.—to be provided with less energy consumption, is applied regardless of the stabilization level. Hence, end-use technologies exhibit consistent benefits even at relaxed stabilization levels.

On the other hand, these efficiency measures are aggregated together with technological improvements that reduce the costs of switching from high-carbon fuels to low-carbon fuels: for example, from gas furnaces to electric heat pumps, or from internal combustion engines to electric cars. Fuel switching is more valuable at more stringent stabilization levels. In contrast, supply technologies—particularly those with high unit costs such as solar and CCS—have only the latter effect, and hence exhibit a sharply decreasing impact under relaxed stabilization levels. The combined result is that end-use technologies move up in the rankings when one shifts from the 450-ppmv to the 550-ppmv stabilization level.

3.5. Conclusion and Discussion

In this study I have used the technology assumptions from a representative scenario exercise (the CCTP scenarios; Clarke et al., 2008) and two long-term CO_2 stabilization pathways (to 450 ppmv and 550 ppmv) to construct a full combinatorial dataset with 768 runs from the Global Change Assessment Model (GCAM). Then this dataset was analyzed from three different perspectives: (1) a broad assessment of the degree of variation in the energy consumption and stabilization costs across all the scenarios in the dataset, to highlight general characteristics of the technology space; (2) an assessment of the ranges of stabilization costs associated with each technology development level, which provided insights into issues of risk management; and (3) an assessment of the *reduction* in stabilization cost associated with improvements in individual technologies, which provided information for normative R&D portfolio analysis that seeks the mix and magnitude of R&D investments that minimizes the costs of stabilization.

The experimental design in this study differs from other types of probabilistic uncertainty analysis in that explicit likelihoods were not assigned to any of the outcomes. Instead, the approach should be seen as a means to explore and understand the associated cost and energy system space associated with potential technological improvements.

By and large, the insights from the analyses confirm and reinforce those of the representative scenario analyses upon which they are based. Technological advancements have a substantial impact on stabilization costs, and the impact is larger under more stringent conditions, such as a lower stabilization targets or lack of advancements in other technologies. Improvements to some particular technologies, most notably CCS, have a

larger impact on stabilization costs than improvements to others. More generally, removing the quantity constraint from a technology, and hence increasing the diversity of available technologies in the market (Blanford and Clarke, 2003; Blanford, 2009), has a larger impact on stabilization costs than incremental reductions in the production costs of existing technologies.

A primary advantage of using the full combinatorial dataset is that it can provide insights into the distributional character of outcomes not available with a representative scenario approach. The dataset revealed the interior of the stabilization cost space from which the representative scenarios were carefully selected to cover the crucial data points. Although these extremes are the most informative scenarios to explore, analyzing the full space allows deeper insights to emerge from an understanding of the distributional characteristics.

For example, the full combinatorial approach provided insights into which technologies might prove most effective at hedging against high-cost outcomes, and which technologies might provide consistent value under different circumstances. In general, advances in supply technologies truncate the high-cost tail of the stabilization cost distribution, which arises with otherwise pessimistic technology outcomes, in conjunction with more aggressive climate goals. A decision maker attempting to minimize the chance of very high stabilization costs would consider these technologies valuable from a risk-based perspective, as part of a hedging strategy for the worst-case possibilities. On the other hand, individual supply technologies yield low value under a more relaxed climate goal and under technology-rich conditions, in large part because of substitution effects.

End-use technologies yield relatively consistent value across the full space, partly because they are by their nature contained in a particular sector, and partly because of the aggregate representation of end-use sectors in the study design. Investments in aggregate efficiency improvements in these sectors provide more stable returns to investment across states of technology and stabilization levels.

The exploration of the implications of advances in different technologies under uncertainty is highly complicated; this study has taken only a small step toward adding to the literature on this topic and unraveling the associated conceptual and methodological issues. Several uses or extensions of the approach taken here could prove valuable moving forward.

One immediate extension of this analysis is presented in McJeon et al. (2011). Following the scenario discovery methodology outlined in Bryant and Lempert (2010), Lempert, Bryant, and Hackbarth of Pardee RAND Graduate School developed am algorithm to identify technology combinations that are crucial in avoiding high stabilization costs. This analysis formally examined each combination of technologies according to their *density*—the fraction of high-cost cases among all cases contained in the combination—and the *coverage*—the fraction of all high-cost cases that are contained in the combination.

The analysis confirmed the critical character of CCS that has been demonstrated in numerous other studies; however, it also identified interaction effects among technologies. For example, it found that energy efficiency technologies in the transportation and buildings sectors, in conjunction with CCS, were critical in determining high-cost outcomes—with transportation being a slightly better predictor of

high-cost outcomes than buildings, when combined with the unavailability of CCS. This result was consistent in both 80th percentile threshold (Fig. 3.6) and in 90th percentile threshold (Fig. 3.7).

Of the remaining supply technologies, only advances in nuclear provided substantial protection against the high costs of fixed CCS, with most of the benefit coming from the initial improvement in nuclear technology from fixed to reference levels, and relatively little additional protection gained by further improvement from reference to advanced (Fig. 3.8).

Other directions of future research include exploration of larger sets of scenarios, to flesh out some of the insights that this initial effort has suggested. This may include extension in terms of (1) the number of technologies and the number of attainable levels for each technology; (2) delays in the development of technologies; and (3) regional heterogeneity (such as technology lag or participation lag in the mitigation regime). It would also be valuable to include uncertainties in underlying socioeconomic drivers such as population and GDP per capita.

Finally, a full-fledged analysis of energy R&D portfolios would combine the results from large-scale ensembles, such as the full combinatorial dataset in this analysis, with a stochastic dynamic programming or robust decision making framework, potentially informed by estimates of required R&D investment level and the associated probabilities of success (Baker et al., 2008c, 2009a, 2009b, 2010). As this study suggests, the consideration of the full range of interactions among different technologies contained in a large number of scenarios in the analyses could more effectively inform public decision making in energy R&D.
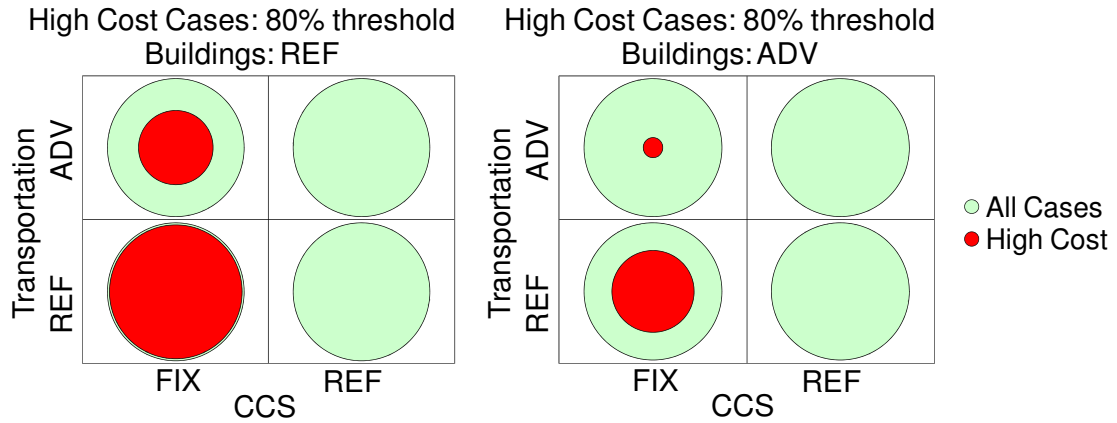
Fig. 3.6. Distribution of cases with costs above the 80th percentile across CCS, transportation, and buildings values for a 450-ppmv target. The outer circle in each square represents all scenarios, and the inner circle the high-cost scenarios, in which the indicated technologies are at the indicated level. For example, the top left square in the left panel includes scenarios in which buildings technologies are at the reference level, transportation technologies are at the advanced level, and CCS is fixed.
Source: McJeon et al. (2011)
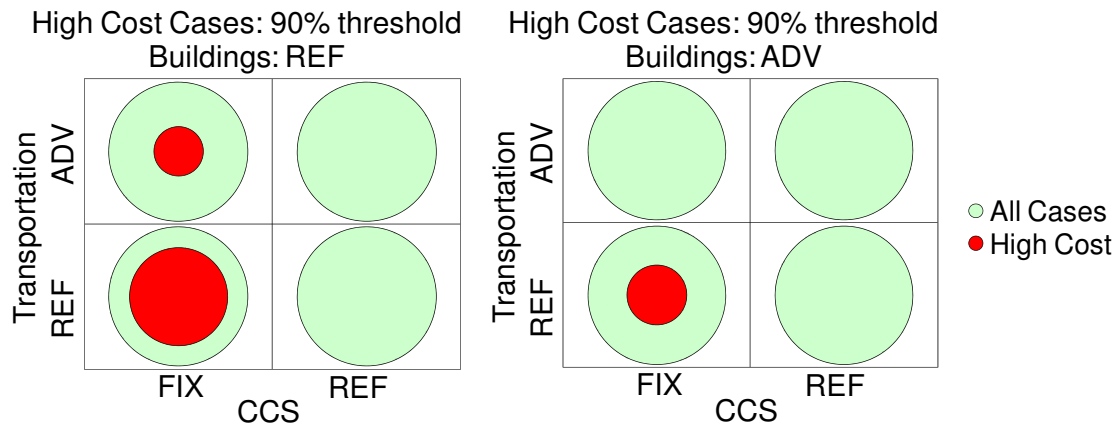
Fig. 3.7. Distribution of cases with costs above the 90th percentile across CCS, transport, and building values for a 450-ppmv target.

Source: McJeon et al. (2011)

High Cost Cases: 80% threshold
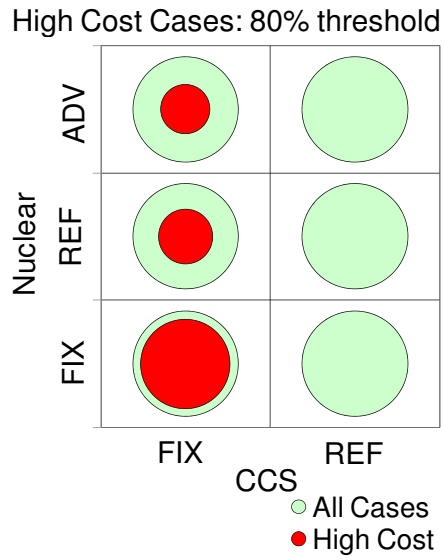
Fig. 3.8. Distribution of cases with costs above the 80th percentile across CCS and nuclear values for a 450-ppmv target.

Source: McJeon et al. (2011)

Chapter 4: R&D Investment Strategy for Low-Carbon Energy Technologies: A Stochastic Dynamic Programming Approach

4.1. Introduction and Background

Globally reducing greenhouse gas (GHG) emissions to mitigate climate change would require either a substantial conservation of energy or a substantial shift in energy sources. However, any major shift away from fossil fuels to low-carbon energy sources would require overcoming currently existing obstacles, including high cost, insufficient capacity, and intermittency.

Successful development of advanced technologies may provide solutions to overcome these obstacles, by reducing capital cost, by providing large-scale deployment option, or by providing efficient energy storage. In turn, these solutions may facilitate the economy to switch away from fossil fuels at a sufficiently low cost and at a sufficiently large scale to mitigate climate change.

In order to make the most efficient use of limited public resources, public R&D investment in technological change should be targeted to maximize the net social benefit per dollar invested. Figure 4.1 shows how the R&D investment for technological change affects climate stabilization policies. Public R&D policy for energy technology is a classic example of decision-making under uncertainty. R&D investments in energy technologies stochastically induce technological change in the forms of cost reductions, capacity increases, emission reductions, and so on. These technological changes, in turn, affect the cost of GHG abatement. The optimal equilibrium emission level is jointly determined by the cost of abatement and the expected damages from climate change. It should be noted that with our current knowledge of climate change, the expected damage

is also highly uncertain. This essay looks into the question of which technologies to invest in, in order to achieve a given level of emission abatement at a lowest cost to the economy. Particularly, this essay focuses on the stochastic process from R&D investments to their impacts on the cost of abatement, the shaded area in Figure 4.1.
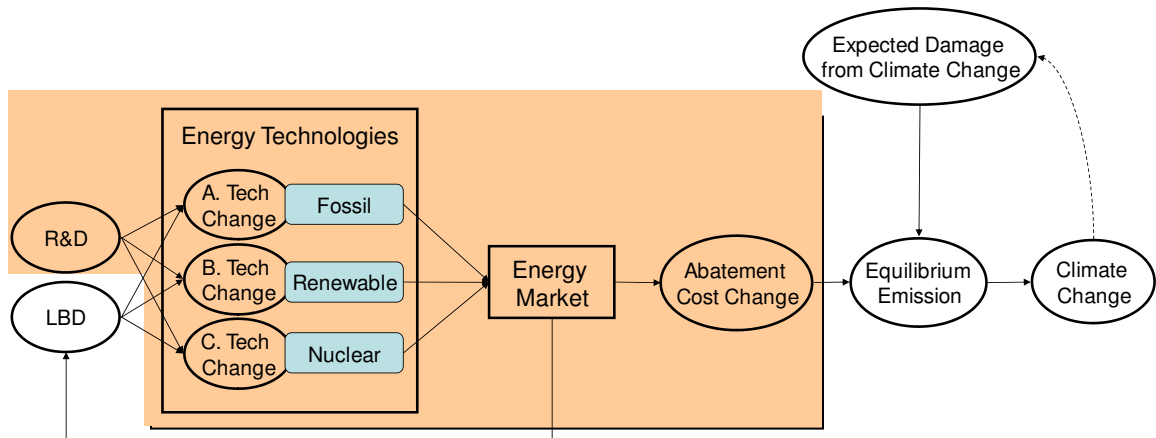
Figure 4.1: Schematics of the impact of technological change on climate stabilization policy

While there have been many studies looking into some portion of this problem, few have attempted to analyze the entire process. On the estimation of abatement costs and the energy market interactions there is a long tradition of research in the field of climate change economics. The Intergovernmental Panel on Climate Change Working Group III has been reviewing these researches for their assessment reports (IPCC, 2007b). The findings from this report, along with other widely referenced studies—such as the Stern Review (2006) and Barker et al. (2006)—suggest that the cost estimates vary widely.

Such wide variations are associated with underlying assumptions of the models used for estimation. These assumptions include: underlying socioeconomic characteristics (Nakicenovic et al. 2000), flexibility in emission abatement regime between sectors or gases (Stern, 2006), and availability of advanced technologies (Richels et al. 2003; Baker et al. 2006). The effect of one particular parameter of interest—technology—on the stabilization cost was the focus of the Pacific Northwest National Laboratory (PNNL) reports (Clarke et al. 2006; Clarke et al. 2008) prepared for the U.S. Climate Change Technology Program (CCTP). The results demonstrate the large differences in the potential for reducing the cost of abatement across different types of technologies. An extension of the study (McJeon et al., 2011) further demonstrated the differences by examining a dataset containing the full combinations of technologies analyzed in the original study.

On the relationship between R&D investment and the probabilities of successful development of specific technologies, Baker, Chon, and Keisler have published a series of papers: solar photovoltaics (Baker et al. 2009a); nuclear (Baker et al. 2008c); carbon capture and storage (Baker et al. 2009b); and battery electric vehicles (Baker et al. 2010). They have explicitly incorporated expert elicitations on the probabilities of success with the expected impact of advanced technologies on the abatement cost. However, the effects of the market interaction among successfully developed advanced technologies were left for future work.

Blanford and Clarke (2003) was one of the first studies analyzing the entire process from the R&D investment to the impact on the cost of abatement. They developed an analytical model involving two investment decision periods and

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probabilistic technology developments. The dynamic aspect of the model was that the success or failure in the first investment period becomes known by the second period, and hence the second period decision is informed by the first. Blanford (2009) further demonstrates this with a numerical simulation model. His results emphasized the importance of clearly understanding the substitution effect among energy technologies and the diversification effect across technologies. The latter effect is driven by the nature of energy technologies and the energy market structure, including decreasing returns to scale, heterogeneous applications, and the low-probability high-returns nature of basic science research.

While highly abstract and simplified in its nature, the model developed in Blanford and Clarke (2003) and Blanford (2009) provides a flexible stochastic framework in which the probabilities of successful development of advanced technologies data and the abatement cost data estimated for different combinations of advanced technology can be combined to generate an optimal R&D portfolio under a given climate mitigation target.

This essay contains one such exercise using the expert elicitation data of Baker, Chon, and Keisler (2008c; 2009a; 2009b; 2010) and the impact of advanced technologies on the abatement cost data of McJeon et al. (2011). These exercises compare *across* technology groups in a comprehensive framework, explicitly incorporating the uncertainties regarding the successful development of technologies.

This essay is organized as follows. The next section presents data for the probabilities of success and estimates for the cost of abatement. The third section develops a simple single decision period stochastic model to identify the optimal

portfolio of technology R&D funding. As an extension, a parametric optimization analysis using the R&D budget level as a varying parameter is presented to show how the optimal technology portfolio changes with respect to budget level. In the fourth section, R&D investment *timing* is added as another dimension to the problem. A stochastic dynamic optimization model is developed to identify the technologies that rank high in the early R&D investment portfolio, and other technologies that could better benefit from a wait-and-see strategy for future periods. The last section closes the essay with a conclusion on the implications of the findings of the analyses and a discussion of future research directions.

4.2. Data

This section describes the data for the probabilities of success and the estimates for the costs of abatement used in the analysis.

4.2.1. Probabilities of Success

The probabilities of success data used in this analysis are obtained from the expert elicitation data from Baker, Chon, and Keisler (2008c; 2009a; 2009b; 2010). The combined probability elicitation results averaged among all experts are presented in Table 4.1. A reprint of the detailed description of the methods used for the expert elicitations are beyond the scope of this paper. Below, I describe additional assumptions and further modifications made specifically for this analysis.

tech group (j)	individual tech (i)	notes	funding level (X)	amount (α) in $mil.	success state (C)	notes	probability of success (p)
Solar PV	SOLx	Inorganic	low	40	SOLa	5¢/kWh	26.8%
			high	80	SOLa	5¢/kWh	43.2%
	SOLy	Organic	low	120	SOLa	5¢/kWh	13.2%
			high	860	SOLb*	3¢/kWh	3.9%
	SOLz	CIGS	high	80	SOLa	5¢/kWh	1.7%
	SOLw*	3rd Gen	high	400	SOLb*	3¢/kWh	1.8%
Carbon Capture and Storage	CCSx	Post-combustion	low	54	CCSa	$30/tC	59.0%
			medium	250			70.1%
			high	540			78.4%
	CCSy	Pre-combustion	low	40	CCSb	$24/tC	2.8%
			medium	160			10.7%
			high	400			22.3%
	CCSz	Chemical Looping	low	20	CCSc	$11/tC	8.0%
			medium	40			29.5%
			high	58			41.8%
Nuclear	NUCx	Light Water Reactor	low	320	NUCb	$1000/kW	21.3%
			medium	480			33.8%
			high	640			60.0%
	NUCy*	Fast Reactor	low	1200	NUCa	$1500/kW	7.5%
					NUCb	$1000/kW	0.1%
			medium	4800	NUCa	$1500/kW	29.5%
					NUCb	$1000/kW	3.0%
			high	16000	NUCa	$1500/kW	37.5%
					NUCb	$1000/kW	22.5%
	NUCz*	High Temp Reactor	low	800	NUCa	$1500/kW	0.9%
					NUCb	$1000/kW	0.3%
			medium	1600	NUCa	$1500/kW	9.2%
					NUCb	$1000/kW	17.0%
			high	3200	NUCa	$1500/kW	10.1%
					NUCb	$1000/kW	30.2%
Transportation Battery	TRNx	Lithium Ion	low	240	TRNa	$200/kWh	17.8%
					TRNb	$125/kWh	12.8%
			high	560	TRNa	$200/kWh	18.4%
					TRNb	$125/kWh	38.4%
	TRNy	Lithium Metal Anodes	low	80	TRNc	$135/kWh	4.3%
					TRNd	$90/kWh	6.6%
			high	320	TRNc	$135/kWh	12.7%
					TRNd	$90/kWh	16.2%

Table 4.1: Key technology characteristics and estimates of the probabilities of success
Modified from Baker, Chon, and Keisler (2008c, 2009a, 2009b, 2010)
* excluded from the technology set used in the final analysis

Solar Photovoltaic Cells

The solar photovoltaic (PV) cell technology characteristics and probabilities of success estimates used in this analysis are based on Baker et al. (2009a). Four types of PV technologies are considered: New Inorganic cells (Inorganic; SOLx), Purely Organic cells (Organic; SOLy), Copper Indium Gallium Selenide cells (CIGS; SOLz), and Third Generation cells (3rd Gen; SOLw).

	Technology	Efficiency (%)	Capital Cost (2005$/m^2)	Lifetime (Years)	LCOE (2005¢/kWh)
SOLx	Inorganic	15%	50	30	5.0
SOLy	Organic (Low)	15%	50	30	5.0
	Organic (High)	31%	50	15	3.0
SOLz	CIGS	15%	50	30	5.0
SOLw	3rd Gen	36%	100	30	2.9

Table 4.2: The success endpoints for Solar PV technologies.
Modified from Baker, Chon, and Keisler (2009a)

Among the considered PV cells, SOLy is the only one using purely organic semiconductors, and all other technologies use inorganic materials. The organic materials hold the promise of low cost, but they must overcome the difficulties in producing sufficiently stable PV panels for the lifetime of 15 or 30 years.

Two funding levels are considered for SOLy. The low funding level is defined as $15 million per year for 10 years; corresponding to $120 million in net present value (NPV) with 5% discount rate. The low funding level targeted producing a 15% efficiency PV cells at $50/m^2 with a lifetime of 30 years, corresponding to a levelized cost of

electricity (LCOE) of 5¢/kWh.[26] The high funding level is defined as $80 million per year for 15 years; corresponding to $860 million in NPV. The high funding level targeted producing a 31% efficiency PV cells at $50/m^2 with a lifetime of 15 years, corresponding to a LCOE of 3¢/kWh.

Among the inorganic PV cells, SOLx and SOLz are classified as the thin-film cells, or the second generation cells to be distinguished from the silicon wafer based first generation PV cells. The thin-film cells have the potential to substantially reduce the material cost. Developing a stable structure with sufficiently high efficiency could make them competitive in the market. SOLz technology is based on the cells using a semiconductor material composed of copper, indium, gallium, and selenium. SOLx technology covers the cells using all other inorganic materials, except the Cadmium Telluride cells. The elicited experts indicated the toxicity concerns regarding Cadmium may preclude large scale deployment. Both inorganic technologies targeted producing a 15% efficiency PV cells at $50/m^2 with a lifetime of 30 years, corresponding to a LCOE of 5¢/kWh. Both technologies were considered for a funding level of $10 million per year for 10 years; corresponding to $80 million in NPV. A low funding level was also considered for SOLx: $5 million per year for 10 years; corresponding to $40 million in NPV.

Lastly, SOLw covers all third generation cells targeted at achieving very high efficiency, including the multi-junction cells and the quantum dot cells. The probabilities were elicited for the cells that could achieve 36% efficiency or higher at $100/m^2 with a lifetime of 30 years, but this technology was excluded from the final analysis due to the

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[26] See Baker et al. (2009a) for detailed calculations.

combination of high levels of funding requirement and low probabilities of success elicited.

In the final analysis, only one level of success at 5¢/kWh LCOE was considered; denoted as SOLa. Successful development of SOLa level PV cells is also assumed to exhibit sufficient stability to be fully competitive in the electricity market by 2050. All 3¢/kWh level of success was excluded due to the combination of high levels of funding requirement and low probabilities of success elicited. The estimate could be reintroduced in future research involving higher total R&D investment level.

Carbon Capture and Storage

The Carbon Capture and Storage (CCS) technology characteristics and probabilities of success estimates used in this analysis are based on Baker et al. (2009b). Three types of CCS technologies are considered: Post-combustion CCS (CCSx), Pre-Combustion CCS (CCSy), and Chemical Looping CCS (CCSz). The original expert elicitations included large number of success endpoints including cost, efficiency, capture rate, operating temperature, compliance with environmental regulations, and so on. For modeling purposes, I reduced the endpoints into three main parameters that are common across the elicited technologies: energy requirement, non-energy cost; and capture rate. The energy requirement parameter measures the amount of energy used in the process of capturing CO_2, *in addition* to the energy already used for power generation. Similarly, the non-energy cost parameter measures the sum of *additional* capital cost and O&M cost needed for capturing CO_2. The capture rate parameter measures the share of CO_2 captured by the technology.

Technology Name	Post-combustion				Pre-combustion				Chemical Looping			
Funding Name - Success State	CCSx - CCSa				CCSy - CCSb				CCSz - CCSc			
Fuel	Coal	Oil	Gas	Bio	Coal	Oil	Gas	Bio	Coal	Oil	Gas	Bio
Energy Requirement GJ/tC	4.7	7.5	10.3	4.7	2.0	3.3	4.5	2.0	0.7	1.0	1.4	0.7
Non-Energy Cost 2005$/tC	30	60	83	30	24	48	66	24	11	22	30	11
Capture Rate %	90	90	90	90	90	90	90	90	90	90	90	90

Table 4.3: The success endpoints for CCS technologies.
Modified from Baker, Chon, and Keisler (2009b)

These probabilities of success are elicited for these parameters, implicitly

assuming a coal-fired powerplant. However, once the technologies are successfully

developed, the same technology could be applied to powerplants fueled by other fossil

fuels as well as biomass. In order to consistently represent the applications of the CCS

technologies in the powerplants fired by other fuels, I assumed the rate of reduction in the

energy requirement and the non-energy cost is the same across different fuel types (see

Table 4.3). The baseline ratios among the different fuel types for these parameters are

obtained from Clarke et al (2008). For oil and gas, the parameters are estimated

conservatively; energy and non-energy cost required per unit capture of CO_2 are assumed

to be higher for these fuels with lower carbon content. On the other hand, the parameters

for biomass-fired powerplants are assumed to be the same as those for coal-fired

powerplants, primarily because both of the fuel types are solid, and hence require similar

processes for the capture (e.g. gasification). Below I present a brief summary of

parameters for coal-fired powerplants used in this analysis. For other fuel types, see

Table 4.3. For extensive descriptions of the parameter calculations, see Baker et al (2009b).

CCSx covers wide range of technologies that involve removing CO_2 from flue gases *after* the fuel has been combusted for electricity generation. The probabilities were elicited for several different methods: membranes, solvents, stimulus, and cryogenic methods. Main challenge for these technologies is finding low-cost materials that are effective and safe for operations. A successful development from any of these methods are assumed to result in a CCSa level of coal-fired CCS powerplant technology characterized by less than 4.7 GJ/tC energy requirement (equivalent to 30% derating), less than \$30/tC additional non-energy cost, and more than 90% capture rate .

Three funding levels are considered for CCSx technology. The low funding level is defined as \$5 million per year for 15 years; corresponding to \$54 million in NPV. The medium funding level starts at \$15 million per year in the first year, linearly increasing to \$30 million per year over the next ten years, and then held constant at \$30 million per year for the last 5 years; corresponding to \$250 million in NPV. Lastly, the high funding level is defined as \$50 million per year for 15 years; corresponding to a \$540 million in NPV.

CCSy technology works in conjunction with combined cycle powerplants, such as coal Integrated Gasification Combined Cycle (coal-IGCC) powerplants or Natural Gas Combined Cycle (NGCC) powerplants. Unlike Post-combustion capture technologies, CCSy removes carbon from syngas *before* the combustion occurs, resulting in a pure stream of hydrogen to be used for electricity generation. Because the separation of carbon from hydrogen occurs early in the process, the energy loss from the capture process could

be made smaller. The challenge is to demonstrate the technology at commercial scale with sufficiently low cost. The probabilities of successful development of a coal-fired CCS powerplant technology (CCSb) were elicited for achieving less than 2.0 GJ/tC energy requirement (equivalent to 10% parasitic energy loss), less than 10% additional capital cost ($24/tC), and more than 90% capture rate.

Three funding levels are considered for CCSy technology: the low-level of $5 million per year for a 10-year investment period, the medium-level of $20 million per year for a 10-year period, and the high-level of $50 million per year for a 10-year period. The NPV of the funding trajectories are $40 million, $160 million, and $400 million, respectively.

While CCSx and CCSy work in conjunction with existing designs of powerplants, CCSz technology involves a powerplant design fundamentally different from the existing ones. Combusting fossil fuels with regular air emits flue gas not only containing CO_2 and H_2O, but also other particles such as NO_x. The existence of these other particles makes it inefficient to separate out CO_2 for sequestration. CCSz instead uses oxidized particles to react with fossil fuels, which is then oxidized to produce flue gases purely consisted of CO_2 and H_2O. H_2O, the water vapor, is then condensed, yielding pure steam of CO_2 to be captured and stored. If the technology can be developed with a particle that is both effective and durable at high temperatures, CO_2 capture can be performed with minimal loss in energy.

The probabilities of successful development (CCSc) were elicited for achieving 5¢/kWh overall LCOE, along with durability under high temperature and compliance with environmental regulations. For the modeling purposes, minimal energy requirement

of 0.7 GJ/tC, additional non-energy cost of $11/tC, and 90% capture rate is assumed to represent LCOE of 5¢/kWh for coal-fired powerplant.

Three funding levels are considered for CCSz technology. Each funding trajectory has two parts: first 5 year investment period with exploratory amount of funding and the next 5 year investment period for a large-scale funding conditional upon successful progress in the first 5 years. The low funding level is defined as $0.5 million per year for the first 5 years and $5 million per year for the next 5 years; corresponding to $20 million in NPV. The medium funding level is defined as $1 million per year for the first 5 years and $10 million per year for the next 5 years; corresponding to $40 million in NPV. The high funding level is defined as $5 million per year for the first 5 years and $10 million per year for the next 5 years; corresponding to $58 million in NPV.

Overall, in all three aspect of the success endpoints, CCSc is (weakly) superior to the other two, and CCSb is (weakly) superior to CCSa. For simplicity, in the event of multiple successes in CCS, I assume only the superior technology will prevail in the energy market. All successful developments of CCS technology are assumed to have fully matured to allow large-scale expansion by 2050, if the levelized costs are competitive.

Nuclear

The nuclear electricity technology characteristics and probabilities of success estimates used in this analysis are based on Baker et al. (2008c). The original expert elicitations covered three nuclear technologies: Light Water Reactor (LWR; NUCx), Fast Reactor (FR), High Temperature Reactor (HTR) and Small Long Lived Core Reactor

(SLLC). The elicited success endpoints included standard technology characteristics such as capital cost and efficiency, as well as a number of unique characteristics such as reduced accident risk, reduced water usage, reduced radioactive waste, and so on.

Due to difficulties in consistently modeling non-monetary characteristics, such as safety and waste disposal, this analysis only modeled capital cost and efficiency. These non-monetary characteristics are the main strengths of Fast Reactor, High Temperature Reactor, and Small Long Lived Core Reactor. For instance, one of the major benefits of Fast Reactor and High Temperature Reactor is substantially reduced radioactive waste (Matthew et al. 2003; Rodriguez et al. 2002). Also, these technologies have different implications in terms of resistance to nuclear weapons proliferation (Ansolabehere et al. 2003). Due in part to the difficulties in modeling these non-monetary issues, as well as the lowest elicited funding levels being an order of magnitude higher than the scope of this analysis, these technologies are excluded from the final analysis. Further research into an accurate understanding of the non-monetary issues could allow for the inclusion of these technologies in future research with higher total R&D investment levels.

The sole remaining nuclear technology, NUCx is a design evolved from the currently common Light Water Reactors. A successful development of the technology is assumed to result in a NUCb level of technology characterized by a substantially lower capital cost: from $2600/kW in 2005 to $1000/kW in 2050. The efficiency of the reactor is assumed to remain at the same level of 32%. The ten-fold reduction in accident risk is not explicitly considered in the model.

Three funding levels are considered for NUCx technology. The low funding level is defined as $40 million per year for 10 years; corresponding to $320 million in NPV.

The medium funding level is defined as $60 million per year for 10 years; corresponding to $480 million in NPV. Lastly, the high funding level is defined as $80 million per year for 10 years; corresponding to a $640 million in NPV.

Transportation Battery

The transportation battery technology characteristics and probabilities of success used in this analysis are based on Baker et al. (2010). Two types of battery technologies are considered: Lithium-ion batteries (Li-ion; TRNx) and Lithium Metal anode batteries (TRNy).

	TRNa: Li-ion low endpoint	TRNb: Li-ion high endpoint	TRNc: Li Metal low endpoint	TRNd: Li Metal high endpoint
Specific energy	150 Wh/kg	200 Wh/kg	200 Wh/kg	600 Wh/kg
Power density	460 W/L	600 W/L	460 W/L	600 W/L
Lifetime	8 years	10 years	8 years	10 years
Recharge rate	6 hours	3 hours	6 hours	3 hours
Capital cost	$200/kWh	$125/kWh	$135/kWh	$90/kWh

Table 4.4: The success endpoints for transportation battery technologies.
Reprinted from Baker, Chon, and Keisler (2010)

TRNx batteries are essentially the same technology as the current generation Li-ion batteries, but with lower costs and increased reliability. Two levels of considered success states are shown in Table 4.4. The low level of success (TRNa) results in a battery at a unit cost less than $200/kWh along with other features including lifetime, recharge rate, specific energy, and power density adequate for transportation use. The high level of success (TRNb) results in better performance across all considered

characteristics; most importantly its unit cost is less than $125/kWh. Either level of success is assumed to result in a Plug-in Hybrid Electric Vehicle (PHEV) that is fully competitive with conventional internal combustion engine vehicle (ICV) by 2050.

Two funding levels are considered for TRNx batteries: the low-level of $30 million per year for a 10-year investment period and the high-level of $70 million per year for a 10-year period. The net present value of the funding trajectories discounted at 5% yields $240 million and $560 million, respectively. Corresponding average probabilities of success from the expert elicitations are shown in Table 4.1.

TRNy batteries are a broad range of battery technologies including both Lithium-Sulfur batteries and batteries with non-sulfur cathodes. Two levels of considered success states are shown in Table 4.4. Each level of success is more aggressive than what would result from the corresponding level of successes in TRNx batteries. The low level of success (TRNc) results in a battery at a unit cost less than $135/kWh along with other features adequate for transportation use. The high level of success (TRNd) attains better performance in all considered characteristics, most importantly its unit cost less than $90/kWh. Either level of success is assumed to result in a Plug-in Hybrid Electric Vehicle (PHEV) that is fully competitive with conventional internal combustion engine vehicle (ICV) by 2050. In addition, the high level of success (TRNd) is assumed to result in a light-weight battery with sufficient specific energy and quick charging cycle that allows a Battery Electric Vehicle (BEV) solely powered by electricity to be fully competitive with ICV by 2050.

Two funding levels are considered for TRNy batteries: the low-level funding of $10 million per year for a 10-year investment period and the high-level of $40 million per

year a 10-year period. The net present value of the funding trajectories discounted at 5% yields $80 million and $320 million, respectively. Corresponding average probabilities of success from the expert elicitations are shown in Table 4.1.

Synthesis

Figure 4.2 shows the probability estimates for all technologies considered in this analysis. The line markers are the original probability elicitation data, and the arrows indicate the existence of another data point not shown in the chart due to scale, but included in Table 4.1. The solid lines denote piecewise linear interpolation of the original data, while the dotted lines indicate extrapolation from the original data.

In order to minimize the potential misuse of the original data, the extrapolations are limited to one $40 million funding unit beyond the original data. The marginal probabilities of the extrapolated portion of SOLx, SOLz, and CCSz on the upper end of the funding level are assumed to be a quarter of immediately preceding estimates. This is a conservative assumption motivated by minimizing misuse of the original data beyond the experts' intent. However, these last unit funding results should be interpreted with due caution.

All but one of the technologies are assumed to start at zero probability with zero additional R&D investment. Given that Baker et al. focused on breakthrough technologies that would otherwise have limited chance of success without additional R&D funding, this is a reasonable assumption. However, CCSx is treated as an exception to this assumption with a 56% probability of success at the zero additional funding level. This decision was motivated by two reasons. First, assuming zero probability of success

in CCS technologies results in a R&D portfolio dominated by all considered CCS technologies. This result is driven by the fact that CCS is the only technology in this analysis that could be utilized for net negative emission energy source in conjunction with biomass electricity. The mere existence of feasible CCS technology, regardless of cost, drives down the stabilization cost substantially under stringent climate target considered in this analysis. Second, some experts consider high-cost CCS to be either already developed to be deployed or well on track for successful development with or without additional funding (Baker et al., 2009b; National Research Council, 2007). If this is the case, assuming zero probability would be a severe underestimation of the technology. For these reasons, the lowest performing CCSx is assumed to have positive probabilities of success even at zero funding level. The marginal probability for the extrapolated region is assumed to be the same as that of the next highest funding level. This modification results in a R&D portfolio less favorable to CCS technologies generally, and to CCSx technology specifically.

With these modifications, the probabilities of success are collected for each unit of $40 million of R&D funding. In order to compare the probabilities with large variances in the elicited level of funding -- ranging from $20 million (CCSz) to $16000 (NUCy) – in a single framework, I limit the scope of this analysis to the most commonly overlapping funding range from 0 to $160 million. Future research may also exclusively focus on the technologies with funding requirements that are an order of magnitude higher than those analyzed here.

Figure 4.2 clearly distinguishes the technologies with high probabilities of success (CCSx; CCSz; and SOLx) and those with low probabilities (SOLz). Many technologies

show overlapping levels of probabilities (TRNx, TRNy, and SOLy; CCSx and NUCx). This is consistent with the intent of the original study of eliciting breakthrough technologies with low probabilities of success that could benefit from additional R&D funding. With such similar probabilities, the priorities among these technologies will be determined by the cost reduction potential of each technology. Also note the general trend of diminishing marginal probabilities with respect to funding level (SOLx, SOLy, and TRNy). Later, this effect is shown to contribute to an R&D diversification strategy across technology groups.
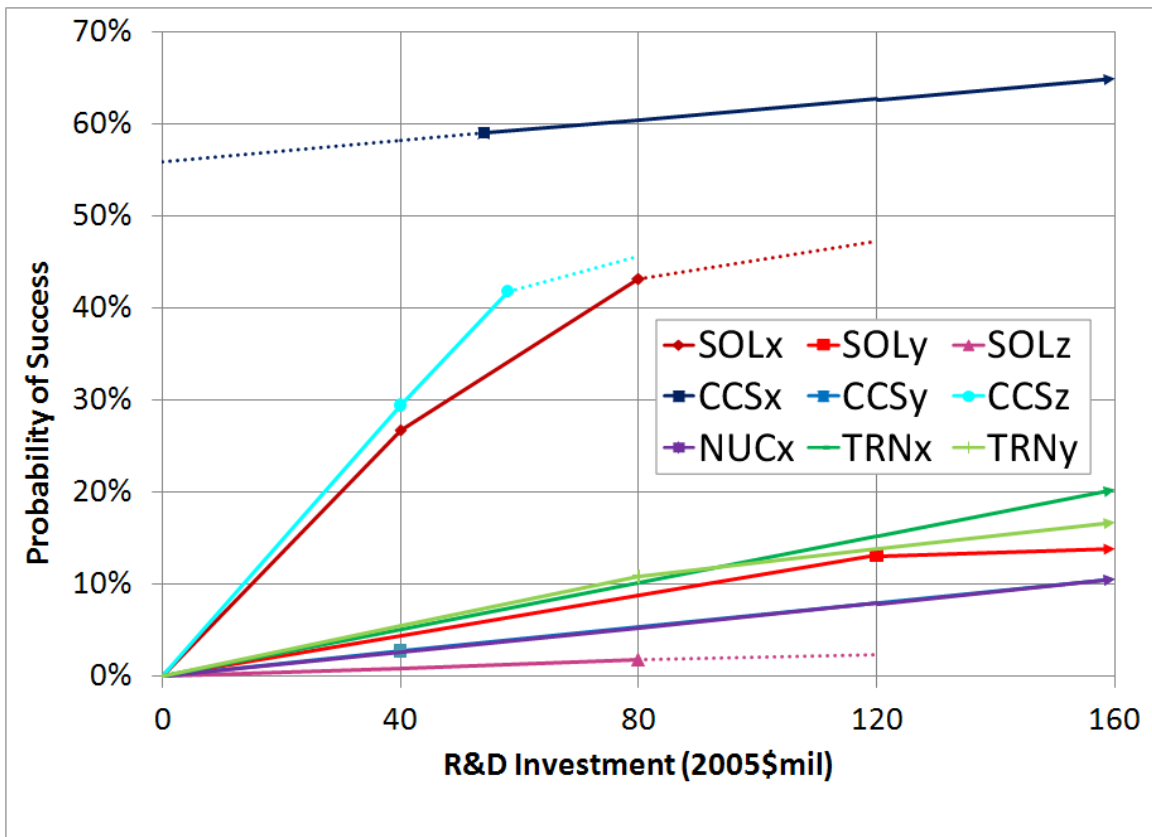
Figure 4.2: The probabilities of success
Modified from Baker, Chon, and Keisler (2008c, 2009a, 2009b, 2010)
*Solid lines denote piecewise linear interpolation.
**Dotted lines denote extrapolation from original data

4.2.2. Stabilization Costs

The costs of stabilizing the CO_2 concentration are calculated using the Global Change Assessment Model (GCAM) version 2.1. GCAM is an integrated assessment model built on the foundations of MiniCAM (Kim et al., 2006; Clarke, et al., 2007; Brenkert et al., 2003), which in turn has its origins from the first model developed by Edmonds and Reilly (1985). GCAM is a dynamic-recursive model, which links a global energy economy model and agricultural land use model with a suite of coupled gas-cycle, climate, and ice-melt models integrated in the Model for the Assessment of Greenhouse-Gas Induced Climate Change (MAGICC). GCAM tracks emissions and concentrations of greenhouse gases and short-lived species.[27] GCAM has been used extensively for global climate change analyses conducted for the Intergovernmental Panel on Climate Change (IPCC), various national governments, and non-governmental organizations.[28]

The economic simulation of GCAM is driven by assumptions about population growth and labor productivity that determine potential economic output in each of 14 regions. GCAM 2.1 is typically solved in a 5-year time step and is used to assess potential future developments to the year 2095. GCAM establishes market-clearing prices for all energy, agriculture and land markets such that supplies and demands for all markets balance simultaneously. That is, there are no excess supplies or demands for land, agricultural products, primary energy, final energy, or energy services.

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[27] GCAM tracks emissions of 15 greenhouse related gases: CO_2, CH_4, N_2O, NO_x, VOCs, CO, SO_2, carbonaceous aerosols, HFCs, PFCs, and SF_6. Each is associated with multiple human activities that are explicitly modeled in GCAM.
[28] A formal documentation of the model can be found at http://www.globalchange.umd.edu/models/gcam.

The GCAM energy system includes primary energy resources, production, energy transformation to final fuels, and the employment of final energy forms to deliver energy services. Energy supplied from depletable resources—fossil fuels and uranium—depends on the abundance and grade of available resources as well as available extraction technologies. These depletable resources exhibit increasing costs in the absence of significant technical change. As more attractive resources are consumed, less attractive resources are exploited and, *ceteris paribus*, costs rise. Renewable resources such as wind and solar are produced from graded renewable resource bases.

Primary energy forms include liquids, gases, coal, bioenergy, uranium, hydropower, solar, and wind energy. Primary energy forms are refined and transformed into end-use energy forms. End-use energy forms include refined liquids, refined gas, coal, commercial solid bioenergy, hydrogen, and electricity. These energy forms are used in the building, industry, and transportation sectors.

GCAM is a technology-rich integrated assessment model. It contains detailed representations of technology options in all of the economic components of the system. Technology choice in GCAM is determined by market competition. Individual technologies compete for market share based on their technological characteristics (efficiency in production from inputs), cost of inputs and price of outputs. GCAM uses a logistic choice framework to determine market shares of different fuels and technologies based on a probabilistic model of the relative prices of the competing fuels or technologies (Clarke and Edmonds, 1993; McFadden, 1974, 1981). This methodology is based on the idea that every market includes a range of different suppliers and purchasers, and each supplier and purchaser may have different needs and may experience different

local prices. Therefore, not all purchasers will choose the same technology because the average price of that technology is lower than the average price of a competing technology. The logistic choice methodology allocates market shares based on prices, but ensures that higher priced goods can gain some share of the market, which is consistent with both empirical observations and economic theory. The logistic choice approach captures the observed heterogeneity of real markets in a stylistic way.

Assumptions for technologies other than the technologies considered in this analysis are based on the reference scenario used for the Climate Change Technology Program (CCTP: Clarke et al. 2008). The basic methodology for estimating the cost of abatement is similar to Baker et al. (2008c; 2009a; 2009b; 2010). However, while those studies focused on the *marginal* abatement cost (MAC) for a specific year 2050, this analysis focuses on the *total* abatement cost (TAC) over the period of 2005 - 2095.

Given a target level of atmospheric CO_2 stabilization and available suite of technologies, the model solves for a cost-minimizing optimal emission path (Peck and Wan, 1996; Hotelling, 1931). It then derives a marginal abatement cost curve, unique for each technology scenario. The total abatement cost for each technology scenario is calculated by integrating the area under the marginal abatement cost curve, and then summing the net present value over the analysis time frame of 2005-2095.[29]

Two stabilization targets are considered: 450 ppmv and 550 ppmv. These levels of stabilization are of particular interest from the research perspective. First, both targets require substantial abatement in the future (see, for example, Figure 4.3; Wigley et al, 1996), and thus the cost of stabilization is sufficiently high to be a social concern.

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[29] Throughout the essay, a 5% real discount rate is used for present value calculations. This applies to both R&D investments as well as to the abatement costs.

Furthermore, high stabilization costs also indicate a large potential for the cost reduction by the introduction of advanced technologies. Second, the low target of 450 ppmv requires substantial abatement in the early periods, while the high target of 550 ppmv abatement is relatively gradual (Nakicenovic et al. 2000; Wigley et al 1996). Hence, the 450 ppmv TAC is often more than a factor of 3 or 4 higher (See Clarke et al. (2007) for comparison under different stabilization levels and McJeon et al. (2011) for the comparison across different technology suites).
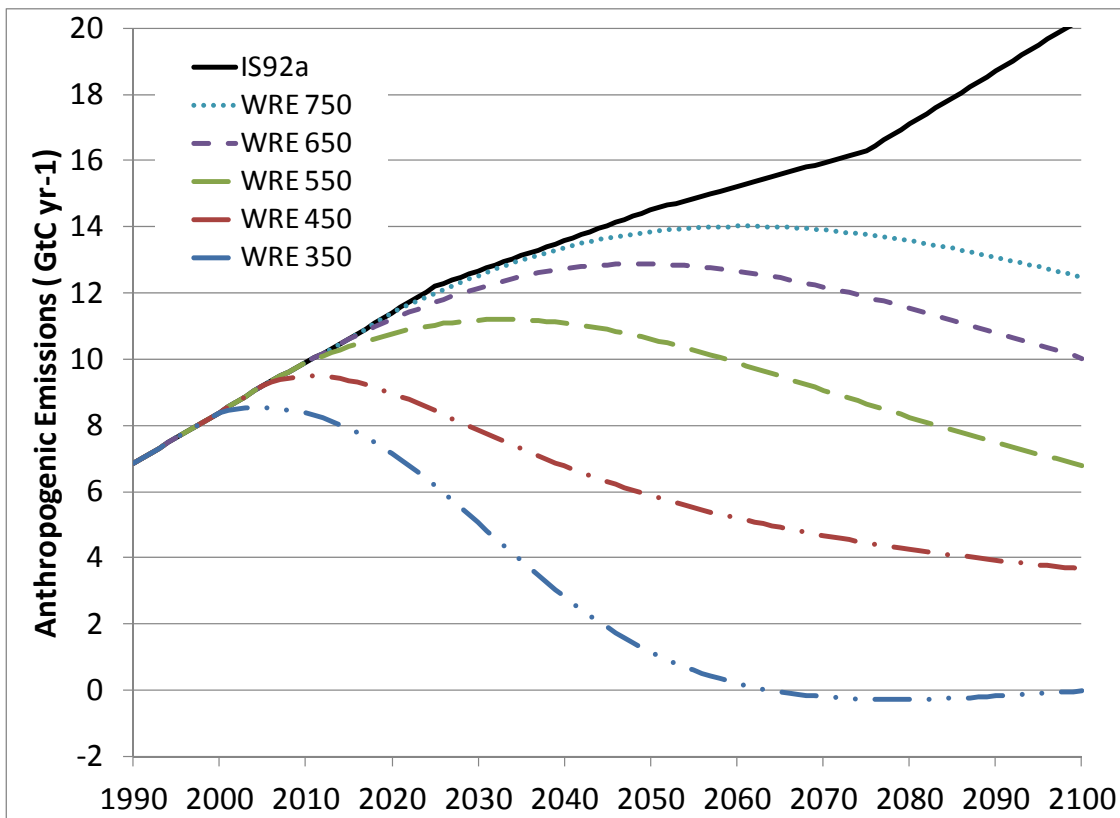
Figure 4.3: Examples of emissions paths under different levels of stabilization
Reproduced from Wigley, Richels, and Edmonds (1996)

(A) 450 ppmv target

		NUCr0					NUCb0				
		TRNr0	TRNa0	TRNb0	TRNc0	TRNd0	TRNr0	TRNa0	TRNb0	TRNc0	TRNd0
SOLr0	CCSr0	12.27	11.90	11.66	11.75	11.25	9.73	9.41	9.20	9.28	8.85
	CCSa0	11.15	10.79	10.57	10.65	10.16	9.07	8.75	8.56	8.63	8.21
	CCSb0	10.25	9.90	9.67	9.75	9.28	8.53	8.23	8.03	8.10	7.67
	CCSc0	9.51	9.16	8.93	9.02	8.54	8.05	7.74	7.53	7.61	7.18
SOLa0	CCSr0	11.87	11.50	11.26	11.35	10.87	9.53	9.21	9.01	9.08	8.64
	CCSa0	10.90	10.53	10.30	10.38	9.90	8.92	8.61	8.40	8.47	8.04
	CCSb0	10.07	9.71	9.48	9.57	9.08	8.42	8.11	7.91	7.98	7.55
	CCSc0	9.37	9.02	8.79	8.87	8.39	7.96	7.65	7.45	7.52	7.09

(A) 450 ppmv target

(B) 550 ppmv target

		NUCr0					NUCb0				
		TRNr0	TRNa0	TRNb0	TRNc0	TRNd0	TRNr0	TRNa0	TRNb0	TRNc0	TRNd0
SOLr0	CCSr0	2.90	2.78	2.71	2.73	2.57	2.11	2.01	1.94	1.97	1.83
	CCSa0	2.70	2.59	2.51	2.54	2.39	2.02	1.92	1.85	1.87	1.73
	CCSb0	2.41	2.30	2.23	2.26	2.11	1.85	1.76	1.69	1.72	1.58
	CCSc0	2.16	2.05	1.99	2.01	1.87	1.69	1.60	1.53	1.56	1.43
SOLa0	CCSr0	2.66	2.54	2.47	2.50	2.35	1.98	1.88	1.82	1.84	1.70
	CCSa0	2.49	2.38	2.31	2.33	2.19	1.90	1.80	1.73	1.76	1.62
	CCSb0	2.24	2.13	2.06	2.09	1.95	1.75	1.65	1.59	1.61	1.48
	CCSc0	2.02	1.92	1.85	1.87	1.73	1.60	1.51	1.45	1.47	1.34

(B) 550 ppmv target

Figure 4.4: Total abatement costs (in trillions of 2005 constant dollars)
* 0 at the end of technology level label (e.g. SOLa0) denotes zero delays in the technology development

The net present values of the total abatement costs for the two stabilization targets under different combinations of successfully developed technologies are shown in Figure 4.4. Several observations bear note. First of all, 450 ppmv costs substantially more than 550 ppmv. Furthermore, 450 ppmv cost *reduction* potential is also substantially more than 550 ppmv.

Second, the technologies have very diverse potential levels of TAC reduction. In general, CCS and NUC technologies show the largest TAC reduction potential, while SOL technologies show the smallest. Also note that the relative strengths of technologies change between the two targets. For example, CCSz has a larger TAC reduction potential under the 450 ppmv target, while NUCb has a larger potential under 550 ppmv target. The next two sections show how these differences drive R&D strategies apart under different stabilization targets.

Third, the TAC reduction potentials of a combination of technologies are not additive (McJeon et al., 2011). This is particularly evident among the electricity generation technologies, which generally behave as (partial) substitutes for one another in the market. For instance, when an advanced CCS has already substantially decreased the TAC, having an additional breakthrough in solar PV technology is worth less than the same breakthrough under the reference scenario with no CCS available.

4.3. Simple Model

Using the probabilities of success data obtained from expert elicitations and the total abatement cost data estimated by a deterministic simulation model, this section develops a simple decision making model under technology development uncertainty.

4.3.1. Model Structure

In the simple model, I assume all funding decisions are made in a single period. The goal of the problem is to minimize the expected net present value of total abatement cost (ETAC) for 450 ppmv. The set of feasible funding decisions (X) are {0, 40, 80, 120,

160} million dollars for each technology denoted with subscript i (note that some technologies have fewer than four funding levels).

$$X \in \{0, \ 40, \ 80, \ 120, \ 160\}^I$$

The state (C) after funding is a unique combination of success and failure levels (S) of each technology group denoted with subscript j (CCS, SOL, NUC, TRN).

$$C \in (\prod_{j \in J} S)$$

For example, if there were a combination of chemical looping CCS success, no success in solar PV, \$1000/kW nuclear success, and a Lithium Metal Anode battery low success, this could be expressed as (CCSc, SOLr, NUCb, TRNc). There are 3 different CCS successes, 1 level of solar PV successes, 1 level of nuclear successes, and 4 different levels of transportation battery success. Including "no success" cases, there are total of 80 = (3+1)(1+1)(1+1)(4+1) different combinations of technology states, each assigned with different total abatement costs as presented in Figure 4.4. In the cases of multiple successes in a technology group, only the superior technology is assumed to prevail. For example, if CCSc and CCSa succeed at the same time, the CCS technology will be assumed to be at the CCSc level of success.

     The expected total abatement cost minimization problem solves:

$$\min_{X} \sum_{C \in (\Pi S)} p(C \mid X) \cdot V(C)$$

$$s.t. \qquad \sum_{i \in I} X_i \leq B$$

$$p(C \mid X) = \prod_{j \in J} p(C_j \mid X)$$

The goal is to minimize the weighted average of the total abatement cost (TAC). This is represented as the sum of probability (p) of reaching a state (C) multiplied by the net present value of the total abatement cost (V), given the technology development state (C). The individual technology group success probabilities are obtained from the expert elicitation. I assume the individual probabilities of success are independent of one another; hence the combined probability of a given combination of success levels in all four technology groups is equal to the product of individual technology group success probabilities of corresponding success levels for each group. The TACs estimated using GCAM. The constraint states that the sum of funding should not exceed the budget. Solving this formulation yields an optimal combination of funding levels for each technology, as well as the minimum expected total abatement cost for a given budget level. Using the parametric optimization approach, we can observe how the optimal portfolio of funding levels and expected total abatement cost changes with respect to the budget level.

4.3.2. Results

Figure 4.5 and Table 4.5 show the results of the parametric optimization analysis. In Figure 4.5, the budget level linearly increases from left to right on the x-axis. Cumulative funding on right y-axis also increases linearly with respect to budget. The colored bars represent the amount optimally funded for each technology. The solid line represents the minimum expected net present value of total abatement cost (ETAC) given the budget level and corresponding optimal R&D portfolio.
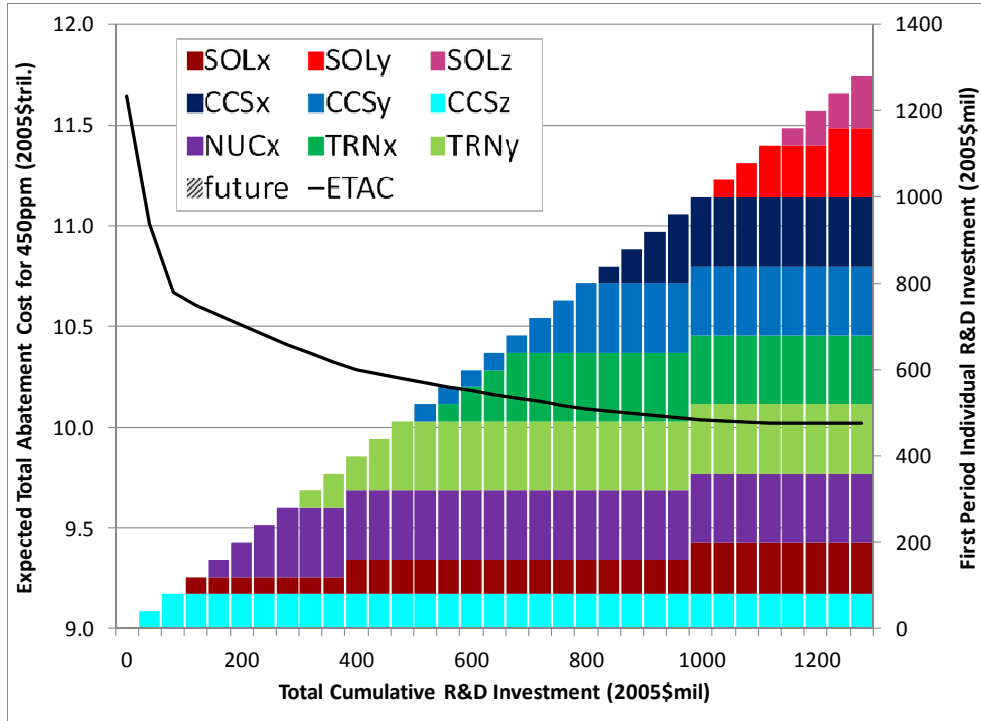
(A) 450 ppmv target
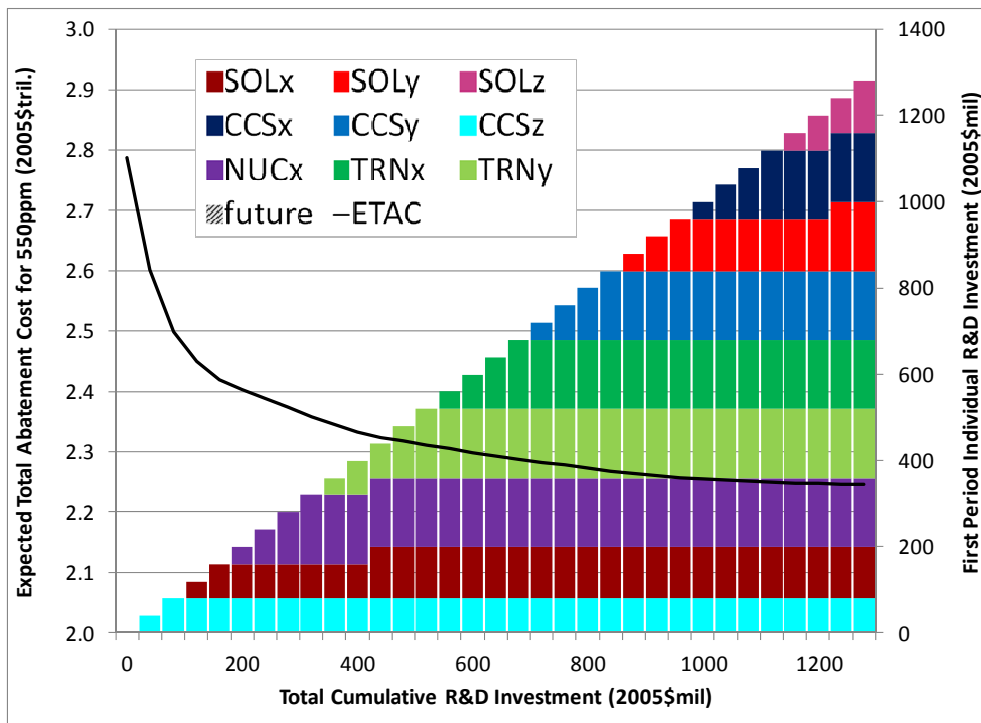
(B) 550 ppmv target

Figure 4.5: Optimal R&D investment portfolio and expected total abatement cost.

Rank	max impact	P of Success with $80M	max impact * P(80)	SDP1
1	CCSz	CCSz	CCSz	CCSz
2	NUCx	SOLx	SOLx	SOLx
3	CCSy	TRNy	NUCx	NUCx
4	CCSx	TRNx	CCSy	TRNy
5	TRNy	SOLy	TRNy	CCSy
6	TRNx	CCSy	CCSx	TRNx
7	SOLx	NUCx	TRNx	CCSx
8	SOLy	CCSx	SOLy	SOLy
9	SOLz	SOLz	SOLz	SOLz

(A) 450 ppmv target

Rank	max impact	P of Success with $80M	max impact * P(80)	SDP1
1	NUCx	CCSz	CCSz	CCSz
2	CCSz	SOLx	SOLx	SOLx
3	CCSy	TRNy	NUCx	NUCx
4	TRNy	TRNx	TRNy	TRNy
5	SOLx	SOLy	CCSy	TRNx
6	SOLy	CCSy	SOLy	CCSy
7	SOLz	NUCx	TRNx	SOLy
8	CCSx	CCSx	CCSx	CCSx
9	TRNx	SOLz	SOLz	SOLz

(B) 550 ppmv target

Table 4.5: Comparison of optimal funding order and other metrics.
* SDP1 denotes the simple model.

Several observations bear note. First of all, the ETAC decreases from $12 tril. ($2.8 tril.) at zero budget to $10 tril. ($2.2 tril.) at $1280 mil. budget for 450 ppmv (550ppmv) target. The savings in ETAC are two to three orders of magnitude higher than the R&D investment amount; implying a large net social gain from the investment under given stabilization targets. Second, the ETAC line shows substantially diminishing returns to scale with respect to investment. For example, the first $200 mil. investment yields $1.1 tril. ($0.38 tril.) in ETAC savings, while the next one yields only $0.23 tril. ($0.072 tril.) savings.

Table 4.5 shows the characteristics of high ranking technologies in terms of R&D funding priority. Top ranking technology CCSz show both high impacts measured in maximum stabilization reduction potential, as well as high probability of success at a

given funding level. On the other hand, the bottom ranking SOLz is characterized by low impact and low probability of success. Two distinct types of high ranking technologies are also observed: medium-impact high-probability technologies (SOLx and TRNy) and high-impact medium-probability technologies (NUCx). The low ranking technologies are the opposite; in the 450 ppmv case, there are low-impact medium-probability (SOLy) and medium-impact low-probability (CCSx).

Table 4.5 also demonstrates the added value of using a model optimizing over the full set of technology combinations (SDP1). Without comprehensively modeling the combinations of technologies, a decision maker could rely on individual data, such as the probabilities of success or the maximum TAC reduction potential (max impact). As the significantly different orders in the table suggest such individual data could be quite far from the optimal order. With both sets of data, the decision maker could do a simple multiplication of the probabilities and the maximum impact potential to yield a more refined investment order. This order turns out to be mostly similar to the optimal order generated by the model. The only differences are the two TRN technologies' movement upward in the optimal portfolio. This difference is consistent with the observation in McJeon et al. (2011) that the maximum impact measurement systematically underestimates the strengths of end-use technologies. End-use technologies generally have limited scopes of impact, such that the maximum impact is limited by the scope. On the other hand, these technologies show relatively narrow variability in their impacts; while supply technologies may lose much of their impacts when other technologies succeed due to substitution effect (CCS vs. NUC), end-use technologies suffer less from such effects (TRN vs. BLD).

4.4. Stochastic Dynamic Programming Model

The model presented in this section adds another dimension, namely the timing of funding, to the previous simple model. Using the stochastic dynamic programming approach, I allow for the possibility of funding some technologies in the future period *after* observing the development of technologies funded in the first period. The objective of this model is to identify which technologies should be funded early on to minimize the expected total abatement cost.

There are advantages and disadvantages to delayed funding. One advantage is related to time-discounting. A dollar in the budget now is worth more than a dollar ten years in the future. One can put the dollar in the bank, and take out the dollar plus accrued interest ten years hence. Or if one had a limited budget and borrowed a dollar today, he would have to pay back the dollar plus interest in the future. In this analysis a 5% real discount rate is used, meaning that a dollar in 2010 is equivalent to 1.63 dollars in 2020.

Another advantage is that the decision maker can observe the state of development in the technologies funded in the first period, and then further optimize using that information (the "wait-and-see" strategy). For example, if the early investment in TRNy successfully resulted in a high performance battery TRNd with a $90/kWh unit cost, then there would be no reason to fund the TRNx technology that would at best yield TRNb battery with a higher $125/kWh unit cost. In other words, the decision-maker can benefit from further optimizing with more information obtained from the first period investment.

On the other hand, the obvious disadvantage of delaying the funding is that the development of the technology would also be delayed. Later development means the technology is not available in the near future, and thus the abatement cost would be higher than in the early development case. Since many energy technologies have lifetimes of several decades, technology developed later may take a long time to replace the technologies developed earlier. The magnitude of the disadvantage not only depends on the potential technology improvement path, but also the stringency of the climate target that may either require substantial abatement in the early periods or only in the later periods.
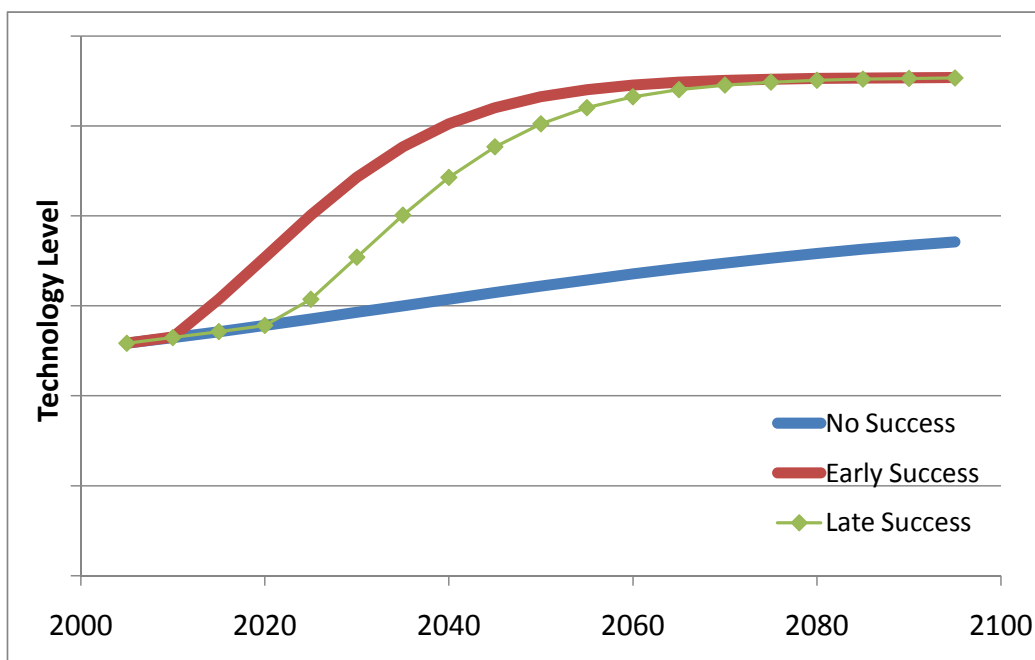
Figure 4.6: Stylistic illustration of delayed success.

A stylistic illustration of delayed success is shown in Figure 4.6. In 2010, an early success technology starts to diverge from the no success trajectory, with accelerated technology advancement. Following Baker et al. (2008c; 2009a; 2009b; 2010), a

successful technology is assumed to be fully matured and integrated in the market by 2050. A late success technology follows the no success trajectory up to 2020, when it starts to diverge with accelerated technology advancement rate ten years behind the early success case. As a result, the late success trajectory asymptotically approaches the early success trajectory.

The advantages and disadvantages of delaying investment may affect technologies differently. Some technologies may be crucial for abatement in the earlier periods, while others are only necessary in the distant future. Also, the existence of a strong substitute within the same technology group could change the optimal funding level for a technology. If there is a high probability of success in a close substitute technology (e.g. CCSz), the benefit of the wait-and-see strategy would be high for the low-performance technology (e.g. CCSx). Sufficiently high benefit of wait-and-see strategy could push down the ranking of the low-performance technology. These aspects make the multiple funding period analyses richer than the simple single period model.

4.4.1. Model Structure

The general structure of the model is similar to the simple model, with one major difference: there are two possible funding periods, 2010 and 2020 denoted with a subscript t. Again, the goal of the problem is to minimize the expected net present value of total abatement cost (ETAC) for the given stabilization target (450 ppmv or 550 ppmv).

The set of feasible funding decisions (X) are {0, 40, 80, 120, 160} for each technology i (note some technologies have fewer than four funding levels).

$$X(C_t) = \left\{ X_t \in \{0,\ 40,\ 80,\ 120,\ 160\}^I \mid \sum_{i \in I} X_{it} \leq B_t \right\}$$

The feasible decision space is further restricted by the constraint that states the sum of funding in a period should not exceed the budget specified for the period.

The state (C) after funding is feasible combinations of success levels and failures of each technology group j (CCS, SOL, NUC, TRN).

$$C_t \in \left(\prod_{j \in J} S_t \right)$$

This formulation is exactly the same as the simple formulation. There are 3 different CCS successes, 1 level of solar PV successes, 1 level of nuclear successes, and 4 different levels of transportation battery success. Including "no success" cases, there are total of 80 = (3+1)(1+1)(1+1)(4+1) different combinations of technology states at the beginning of the second period, each assigned with different total abatement costs presented in Figure 4.4.

In addition to the 80 states, each success level has a delayed success possibility after the second period investment. Now there are 6 different CCS successes, 2 level of solar PV successes, 2 level of nuclear successes, and 8 different levels of transportation battery success. Including "no success" cases, there are total of 567 = (3+3+1) (1+1+1) (1+1+1) (4+4+1) different combinations of technology states at the beginning of the final period, each assigned with different total abatement costs. The entire dataset of estimated TAC is for the two stabilization targets—total of 1134 data points—are presented in Figure 4.7 and Appendix 1.
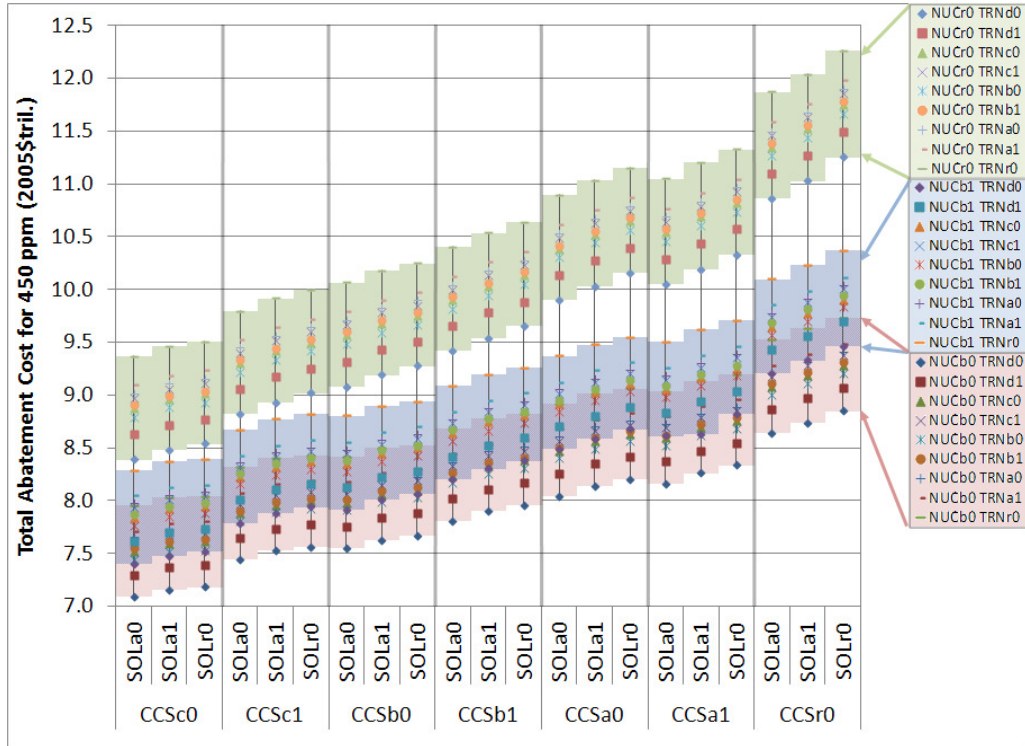
(A) 450 ppmv target
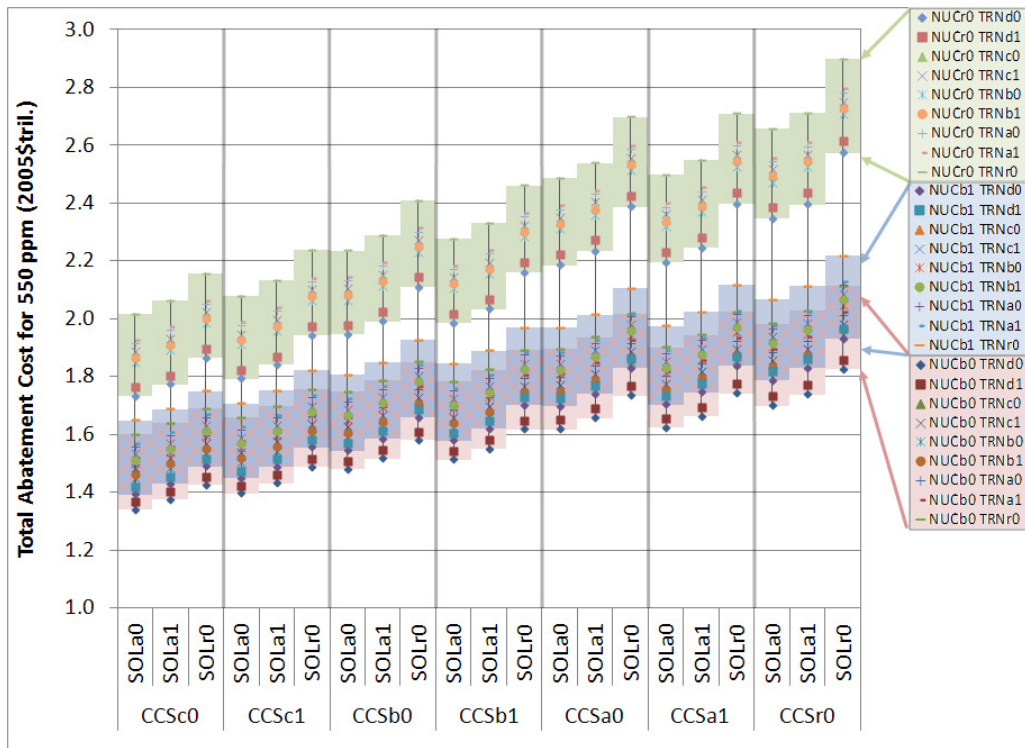
(B) 550 ppmv target

Figure 4.7: Total abatement cost with delayed technology development.

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The number of periods delayed is denoted with a numbered suffix at the end of the technology label. For example, the first period success of SOLa is labeled SOLa0 (for zero delay). The second period success of NUCb is labeled NUCb1. This labeling scheme is designed to allow more investment periods to be added in the future research. For example, if there were a combination of delayed chemical looping CCS success, no success in solar PV, immediate $1000/kW nuclear success, and a delayed Lithium Metal Anode battery low success, this could be expressed as (CCSc1, SOLr0, NUCb0, TRNc1). In the case of multiple successes in a technology group, I assumed only the superior technology would prevail.

The expected total abatement cost minimization problem solves:

$$V_t(C_t) = \min_{X_t \in X(C_t)} E\{V_{t+1}(C_{t+1}) \mid C_t, X_t\}$$

Specifically for the first and the second period, the problem could be elaborated as:

$$V_1(C_1) = \min_{X_1 \in X(C_1)} E\{V_2(C_2) \mid X_1\} = \min_{X_1 \in X(C_1)} \sum_{C_2 \in (\Pi S_2)} p_1(C_2 \mid X_1) V_2(C_2)$$

$$V_2(C_2) = \min_{X_2 \in X(C_2)} E\{V_3(C_3) \mid X_2\} = \min_{X_2 \in X(C_2)} \sum_{C_3 \in (\Pi S_3)} p_2(C_3 \mid X_2) V_3(C_3)$$

$$p_t(C_{t+1} \mid X_t) = \prod_{j \in J} p_t(C_{jt+1} \mid X_t)$$

The probability of reaching a state (C) given a funding combination (X) is denoted with p. The combined probability is the product of probabilities in each group. V is the ETAC given the state (C), and in the 3rd period it is the TAC estimated from GCAM. The second period ETAC (V_2) is the minimized ETAC in the third period, which is equivalent to the sum of probability (p) of reaching a state (C_3) multiplied by the net present value of

total abatement cost (V_3); given technology development state (C_3). Each combination of state at the beginning of period 2 (C_2) yields an optimal combination of funding levels (X_2) and the minimum ETAC (V_2).

Recursively, the first period ETAC (V_1) is the minimized ETAC in the second period, which is equivalent to the sum of probability (p) of reaching a state (C_2) multiplied by the ETAC derived from the second period optimization above (V_2), given technology development state (C_2). Since the state at the beginning of period 1 (C_1) is given as a reference level for all technology groups, solving the first period optimization problem yields a unique optimal combination of funding levels (X_1) and a unique minimum ETAC (V_1).

The budget constraint is embedded in the feasible funding decision set. The stochastic dynamic programming would yield an optimal combination of first period funding levels, as well as the expected total abatement cost *for any given* combination of first and second period budget levels. Using a parametric optimization approach, we can observe how the optimal combinations of first period funding levels and expected total abatement cost change with respect to first and second period budget level.

4.4.2. Results

For the purpose of illustration, here I present the result for $1000 mil. in total discounted R&D investment budget. This example illustrates the optimal balance between the first and the second period budget.

Figure 4.8 shows 25 different allocations of the fixed $1000 mil. total discounted R&D budget. The first period portion of the budget increases from left to right on the x-

axis. The individual funding level is shown on the right y-axis. The diagonal patterned bar labeled "future" denotes the budget allocated for the second period.

The expected total abatement cost (ETAC) is plotted on the left y-axis. Notice that the right-most data point is identical to the $1000 mil. data point in the single period model (Figure 4.5). Neither the full allocation of the budget to the first period (1000, 0) nor the full allocation to the second period (0, 1000) minimizes the ETAC. For both stabilization targets, (680, 320) budget allocation is shown to be the ETAC-minimizing case under the $1000 mil. total discounted budget; henceforth this ETAC-minimizing budget allocation is referred to as the optimal R&D investment portfolio. The solution for the optimal portfolio being located in the interior of the feasible allocation space is consistent with the observed diminishing returns in probabilities of success (Figure 4.2) as well as the presence of the advantages and disadvantages discussed earlier in this section. Formally estimating the optimal budget allocation between present and future is a value added to the analyses focusing on a single period. Only through a formal analysis of the delayed technology development, could a decision maker make an informed decision on the optimal budget allocation between the present and future.

Figure 4.9 shows the optimal R&D investment portfolio for varying levels of total discounted budget. The budget level linearly increases from left to right on the x-axis. Cumulative funding on right y-axis also increases linearly with respect to budget. The colored bars represent the amount optimally funded for each technology. The diagonal patterned bar labeled "future" denotes the optimal budget allocation for the second period. The solid line represents the minimum expected net present value of total abatement cost (ETAC) given the budget level and corresponding optimal budget allocation and optimal

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R&D portfolio. Notice that the data point for the $1000 mil. total discounted budget is identical to the minimum ETAC yielding budget allocation in the Figure 4.8: (680, 320). Figure 4.9 is essentially a collection of ETAC-minimizing budget allocations from 50 different versions of Figure 4.8, with varying total discounted budget.

Several observations bear note. First of all, generally speaking, 60-70% of the total budget is optimally allocated for the first period. Again, this optimal intertemporal allocation result is one important contribution that would not be available without formally modeling the delayed technology development.

Second, the ETAC decreases from $12 tril. ($2.8 tril.) at zero budget to $9.4 tril. ($2.0 tril.) at $2000 mil. budget for the 450 ppmv (550ppmv) target. The savings in ETAC are two to three orders of magnitude higher than the R&D investment amount; implying large net social gain from the investment under given stabilization targets. The ETAC line also shows substantially diminishing returns to scale with respect to investment.

Table 4.6 shows the first-period R&D investment priority rankings of the considered technologies. First, notice that the rank order is almost identical between the single period model (SDP1) and the two-period model (SDP2). This implies that the simple model with much smaller computing power requirement could be used as a reasonable substitute for generating an optimal R&D portfolio for the first period *if the budget allocation across time is not the main concern*. Such a situation could arise, for example, when the budget allocation and timing are exogenously specified by a legal statute instead of being flexible and endogenously determined for economic efficiency.

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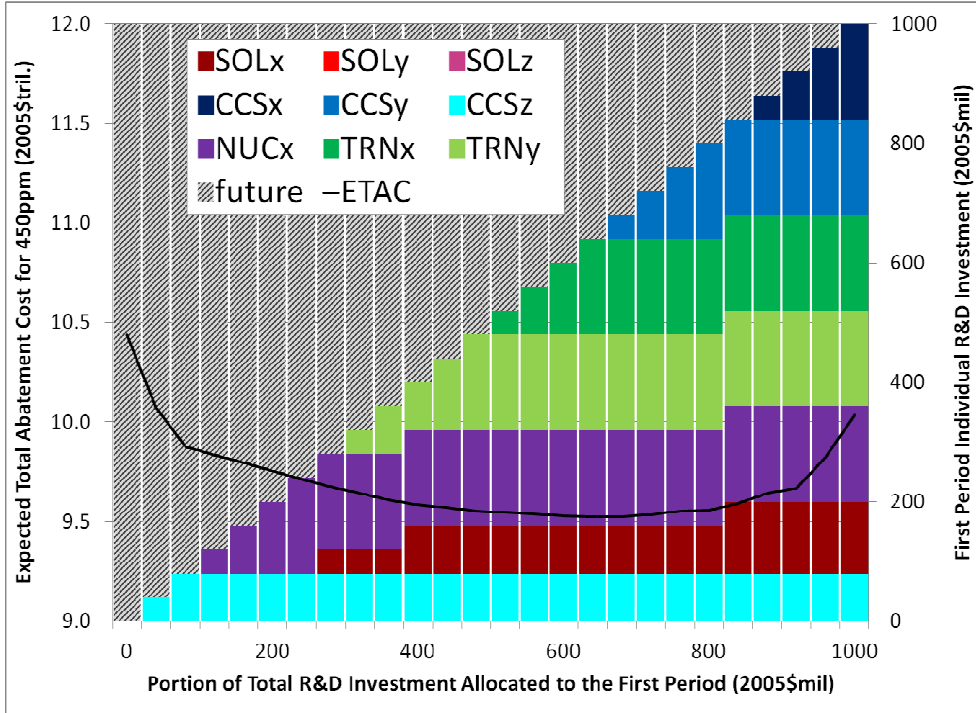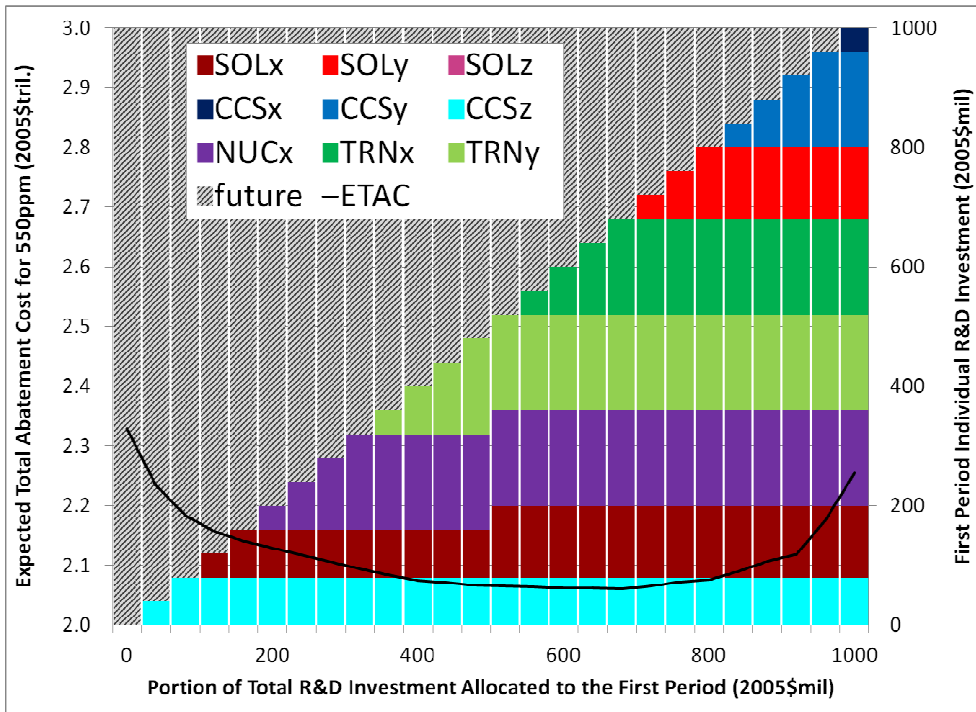
(A) 450 ppmv target

(B) 550 ppmv target

Figure 4.8: Two-period budget allocations and expected total abatement cost for $1000 mil. total discounted R&D budget.

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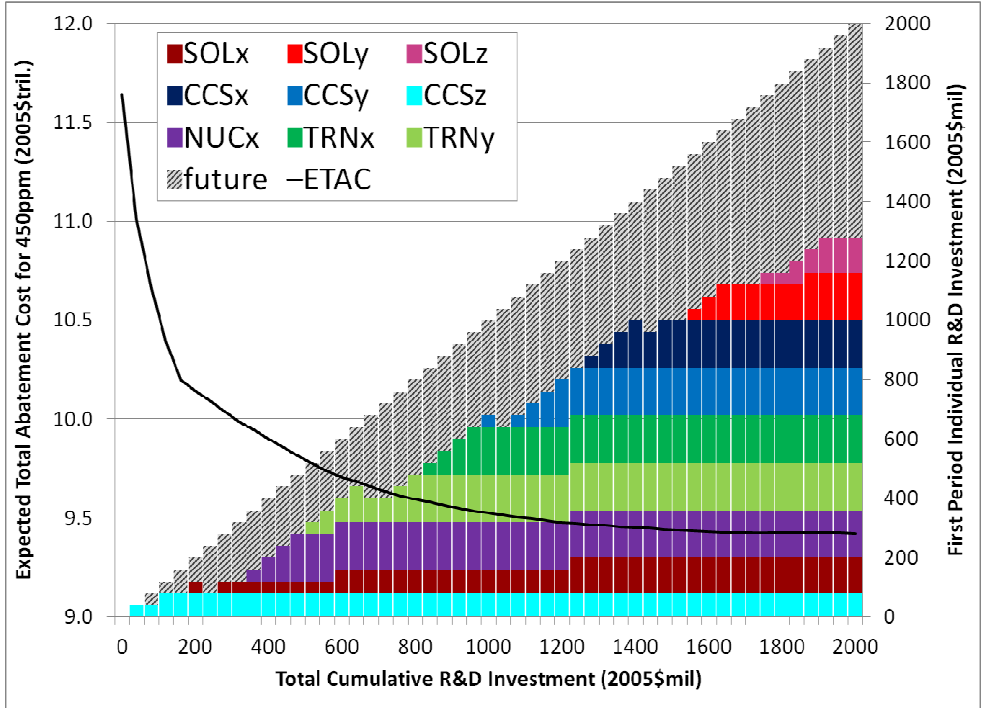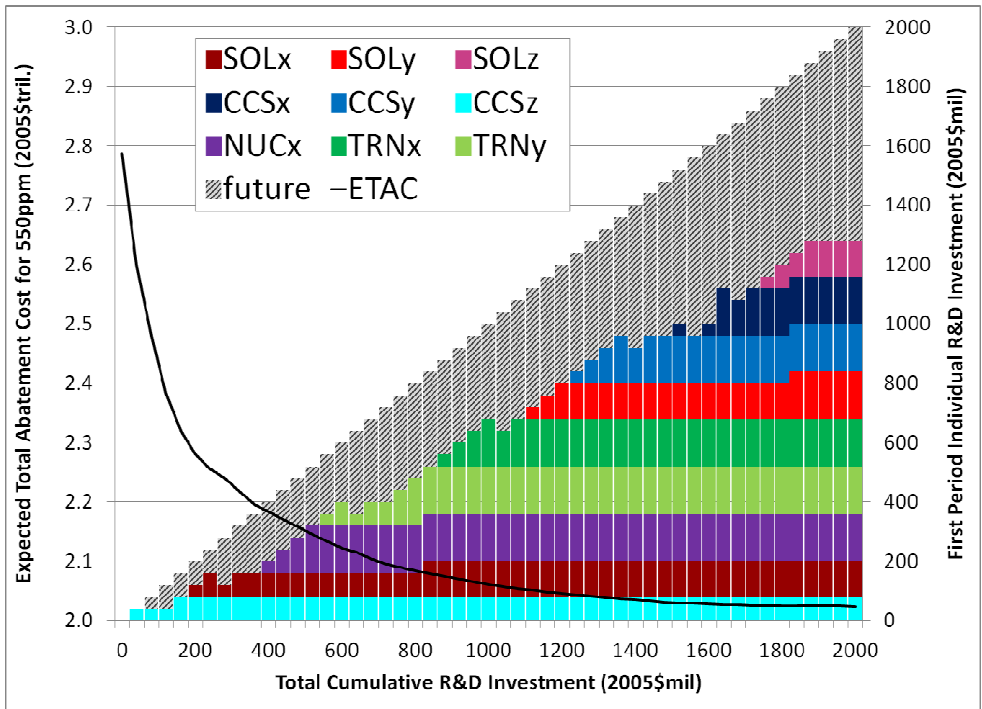
(A) 450 ppmv target

(B) 550 ppmv target

Figure 4.9: Optimal R&D investment portfolio and expected total abatement cost for the two-period stochastic dynamic programming model.

(A) 450 ppmv target

Rank	max impact		Marginal P of Success		max impact * Marginal P		SDP1		SDP2	
1	CCSz	40	CCSz	40	CCSz	40	CCSz	40	CCSz	40
2	CCSz	80	SOLx	40	CCSz	80	CCSz	80	CCSz	80
3	NUCx	40	SOLx	80	SOLx	40	SOLx	40	SOLx	40
4	NUCx	80	CCSz	80	NUCx	40	NUCx	40	NUCx	40
5	NUCx	120	TRNy	40	NUCx	80	NUCx	80	NUCx	80
6	NUCx	160	TRNy	80	NUCx	120	NUCx	120	NUCx	120
7	CCSy	40	TRNx	40	NUCx	160	NUCx	160	NUCx	160
8	CCSy	80	TRNx	80	SOLx	80	TRNy	40	TRNy	40
9	CCSy	120	TRNx	120	CCSy	40	TRNy	80	TRNy	80
10	CCSy	160	TRNx	160	CCSy	80	SOLx	80	SOLx	80
11	CCSx	40	SOLy	40	CCSy	120	TRNy	120	TRNy	120
12	CCSx	80	SOLy	80	CCSy	160	TRNy	160	TRNy	160
13	CCSx	120	SOLy	120	TRNy	40	CCSy	40	TRNx	40
14	CCSx	160	SOLx	120	TRNy	80	TRNx	40	TRNx	80
15	TRNy	40	TRNy	120	CCSx	40	TRNx	80	TRNx	120
16	TRNy	80	TRNy	160	CCSx	80	TRNx	120	TRNx	160
17	TRNy	120	CCSy	40	CCSx	120	TRNx	160	CCSy	40
18	TRNy	160	NUCx	40	CCSx	160	CCSy	80	CCSy	80
19	TRNx	40	NUCx	80	TRNx	40	CCSy	120	CCSy	120
20	TRNx	80	NUCx	120	TRNx	80	CCSy	160	CCSy	160
21	TRNx	120	NUCx	160	TRNx	120	CCSx	40	SOLx	120
22	TRNx	160	CCSy	80	TRNx	160	CCSx	80	CCSx	40
23	SOLx	40	CCSy	120	TRNy	120	CCSx	120	CCSx	80
24	SOLx	80	CCSy	160	TRNy	160	CCSx	160	CCSx	120
25	SOLx	120	CCSx	40	SOLy	40	SOLx	120	CCSx	160
26	SOLy	40	CCSx	80	SOLy	80	SOLy	40	SOLy	40
27	SOLy	80	CCSx	120	SOLy	120	SOLy	80	SOLy	80
28	SOLy	120	CCSx	160	SOLx	120	SOLy	120	SOLy	120
29	SOLy	160	SOLz	40	SOLz	40	SOLz	40	SOLz	40
30	SOLz	40	SOLz	80	SOLz	80	SOLz	80	SOLz	80
31	SOLz	80	SOLy	160	SOLy	160	SOLy	160	SOLy	160
32	SOLz	120	SOLz	120	SOLz	120	SOLz	120	SOLz	120

(B) 550 ppmv target

Rank	max impact		Marginal P of Success		max impact * Marginal P		SDP1		SDP2	
1	NUCx	40	CCSz	40	CCSz	40	CCSz	40	CCSz	40
2	NUCx	80	SOLx	40	CCSz	80	CCSz	80	CCSz	80
3	NUCx	120	SOLx	80	SOLx	40	SOLx	40	SOLx	40
4	NUCx	160	CCSz	80	SOLx	80	SOLx	80	SOLx	80
5	CCSz	40	TRNy	40	NUCx	40	NUCx	40	NUCx	40
6	CCSz	80	TRNy	80	NUCx	80	NUCx	80	NUCx	80
7	CCSy	40	TRNx	40	NUCx	120	NUCx	120	NUCx	120
8	CCSy	80	TRNx	80	NUCx	160	NUCx	160	NUCx	160
9	CCSy	120	TRNx	120	TRNy	40	TRNy	40	TRNy	40
10	CCSy	160	TRNx	160	TRNy	80	TRNy	80	TRNy	80
11	TRNy	40	SOLy	40	CCSy	40	SOLx	120	TRNy	120
12	TRNy	80	SOLy	80	CCSy	80	TRNy	120	TRNy	160
13	TRNy	120	SOLy	120	CCSy	120	TRNy	160	SOLx	120
14	TRNy	160	SOLx	120	CCSy	160	TRNx	40	TRNx	40
15	SOLx	40	TRNy	120	SOLy	40	TRNx	80	TRNx	80
16	SOLx	80	TRNy	160	SOLy	80	TRNx	120	TRNx	120
17	SOLx	120	CCSy	40	SOLy	120	TRNx	160	TRNx	160
18	SOLy	40	NUCx	40	SOLx	120	CCSy	40	SOLy	40
19	SOLy	80	NUCx	80	TRNx	40	CCSy	80	SOLy	80
20	SOLy	120	NUCx	120	TRNx	80	CCSy	120	SOLy	120
21	SOLy	160	NUCx	160	TRNx	120	CCSy	160	CCSy	40
22	SOLz	40	CCSy	80	TRNx	160	SOLy	40	CCSy	80
23	SOLz	80	CCSy	120	TRNy	120	SOLy	80	CCSy	120
24	SOLz	120	CCSy	160	TRNy	160	SOLy	120	CCSy	160
25	CCSx	40	CCSx	40	CCSx	40	CCSx	40	CCSx	40
26	CCSx	80	CCSx	80	CCSx	80	CCSx	80	CCSx	80
27	CCSx	120	CCSx	120	CCSx	120	CCSx	120	CCSx	120
28	CCSx	160	CCSx	160	CCSx	160	CCSx	160	CCSx	160
29	TRNx	40	SOLz	40	SOLz	40	SOLz	40	SOLz	40
30	TRNx	80	SOLz	80	SOLz	80	SOLz	80	SOLz	80
31	TRNx	120	SOLy	160	SOLy	160	SOLy	160	SOLy	160
32	TRNx	160	SOLz	120	SOLz	120	SOLz	120	SOLz	120

Table 4.6: Comparison of optimal funding orders for single-period model (SDP1) and two-period model (SDP2).

However, if the optimal budget balance between the present and the future is the issue, a formal modeling of delayed technology development is still required.

Second, there still remain some changes in the rank order. For example, in the 450 ppmv target case, the first unit of CCSy investment moves behind the TRNx investments. Also, the last unit of SOLx investment moves ahead of CCSx investments. Similar movements are observed for the 550 ppmv target case, with TRNy and SOLy being the beneficiaries.

No simple rule-of-thumb is observed from the changes in the rank-order. Basically, the major determinants of the ranking are still the probability of success and

the potential impact. In many cases, the combined magnitude of these two factors is sufficiently different, such that additional factors do not change the rank order. For example, the top ranking CCSz show high impact measured in maximum stabilization reduction potential and high probability of success at a given funding level. On the other hand, the bottom ranking SOLz has low impact and low probability. These technologies are unlikely to change their rankings. Similar statements can be made for frequent high rankers SOLx (low-impact high-probability), NUCx (high-impact low-probability), and TRNy (medium-impact medium-probability).

However, some local observations could be made where the combined effects of probability and impact of multiple technologies are within a comparable range. Take SOLx for example. SOLx shows a textbook example of diminishing returns; while the potential impact remains the same, the probability exhibits diminishing returns with respect to R&D investment. As a result, SOLx investment units are spread widely across high-medium-low rankings.

In the 450 ppmv target, the last unit of SOLx-120 investment moves up in ranking because CCSx is more vulnerable to the wait-and-see option, as the success in a more advanced CCSz or CCSy would "mute" the success in CCSx. If any of the two leading CCS succeeds in the first period, it would be meaningless to have invested in low-performance CCSx. On the other hand, SOLx-120 benefits from being the leading technology in its group, such that it is not subject to the risk of being muted by a success in another technology in its group. As a result, SOLx-120 moves ahead of CCSx investments in the first-period investment, and CCSx is better suited for wait-and-see option.

More generally, having the second-period adjustment option forces the portfolio towards *diversification across different technology groups*, such that at least one technology from each group gets a chance to succeed. A low-ranking technology within a technology group is the most vulnerable to the wait-and-see option, when the technology is highly substitutable because the technologies are otherwise highly homogenous, or when the high-ranking substitute has high probability of success.

In contrast, some high-ranking technologies within a homogenous group benefit from a concentration of R&D investment. Consider the two TRN technologies. TRNy exhibits larger impact and higher marginal probability for the funding level up to $80 mil. compared to TRNx. However, the higher funding levels for TRNy exhibit diminishing marginal probability of success. Hence, a simple product of maximum impact and marginal probability results in high rank orders for TRNy-40 and TRNy-80, medium rank orders for all TRNx units, and low rank orders for TRNy-120 and TRNy-160. However, when assessed through a full stochastic optimization, all funding levels for TRNy move ahead of TRNx.

The reason can be explained in a simple single period example. Suppose the first two units of TRNy have 50% chance of success. For simplicity, assume the impact is identical for TRNy and TRNx. Next two units of TRNy have 20% marginal probability of success, while the first two units of TRNx have 30% marginal probability of success. If all four units are invested in TRNy the overall probability of success is [70% = 50% + 20%]. On the other hand, if we diversify and invest two units to TRNy and two units to TRNx, the overall probability of success is [65% = 50% + 30% − (50% * 30%)]. The last term is adjusting for overlapping success, in which case the inferior technology becomes

obsolete. Clearly, investing all four units in TRNy is more efficient choice. This dynamic applies to any homogenous technology group with heavily overlapping applications.

In summary, multi-period optimization fully utilizing the probabilities of success data and all combinations of the impact data pushes the optimal R&D investment portfolio towards more diversification across different types of technologies, but more concentration among technologies within a homogenous technology group.

4.5. Conclusion and Discussion

In the last few years, we have been getting an influx of high quality data from the two frontiers of low-carbon energy technology research: one on the probabilities of technology success data (Baker et al., 2008c, 2009a, 2009b, 2010), and the other on the estimated cost of atmospheric CO_2 stabilization from technologically detailed models (Clarke et al., 2008; McJeon et al., 2010). A natural integration of these datasets could be done with a number of different methods. In this essay, I chose stochastic dynamic programming as a decision-making tool incorporating the datasets in order to determine the optimal R&D investment portfolio under specified climate stabilization targets. Using expert elicitation results for four technology groups (carbon capture and storage, photovoltaic cells, nuclear electricity, and transportation batteries) and abatement cost estimates from the GCAM integrated assessment model, this analysis identified which technologies should be given R&D funding priorities in order to achieve the 450 ppmv or the 550 ppmv stabilization target at the lowest possible cost. In this exercise, the results generally point to R&D portfolios that are diversified across considered technology groups, with a relatively strong emphasis on CCS.

The significance of the specific results notwithstanding, they must be treated with caution, considering the caveats and the restrictive assumptions surrounding the analysis. First of all, this analysis takes the expert elicitation results at their face value. There could easily be a shared bias among specific technology experts that pushes the elicitation results up or down. A cross validation of the independent probability assessments could enhance future analysis.

Second, this analysis limited its scope to the 9 technologies that have shared range of elicited R&D funding. The technologies and funding levels that require investment an order of magnitude higher than the maximum specified amount were excluded from the analysis. An additional analysis involving the technologies with higher investment requirements may reveal additional insights not available from this analysis.

Third, the analysis exclusively focused on technology uncertainty, particularly in the economic aspect of the technologies. Non-economic aspects of a technology – such as social acceptance of a new technology – as well as the socioeconomic development in the pattern of energy use are key factors in the climate stabilization cost uncertainty. While focusing only on one aspect of uncertainty enhances clarity of the issue, it could also make the results less robust.

This analysis is only a first step in developing an internally consistent method of identifying the R&D investment priorities across energy technologies in order to minimize the cost of climate stabilization. Further extensions in the following areas would enhance the quality of the analysis. First, a broader set of technologies, particularly end-use efficiency technologies, could be added to the portfolio. It has been noted that the demand-side technologies, such as fuel efficient vehicles or appliances, have a very

different effect on abatement costs as compared to the supply-side technologies, which constituted the majority of technologies analyzed here.

Second, the representation of uncertainty resolution could be made more realistic. One way to do this is instead of using a binary success or failure representation of a technology, a partial success could be included as feasible state level. In this formulation, the decision maker would be allowed to observe the progress of a technology's development, and then either to continue the funding if the progress is promising, or to stop the funding if the progress is unlikely to bear fruit in the following periods.

Moreover, a technology-specific "learning from failure" effect could also be better represented. For example, with failure in some technology development, we may exhaust the investment option and hence lower the probability of success in the next period. For example, a solar PV cell may use a very specific material, and if initial R&D revealed that the material was insufficiently durable in high temperature conditions, this failure may once and for all exhaust the original probability of success. In contrast, with some failures, scientists may learn more about the process and get that much closer to a successful development in the next period. For example, the initial R&D may succeed in enhancing safety of a Li-ion battery, but fail to sufficiently reduce the cost. The next period R&D may piggyback on the safety mechanism developed beforehand, and exclusively focus on the cost reduction, raising the probability of success. Better understanding the differences in the "learning from failure" effect could help better represent the second period probability of success matrix.

Climate change and technology development are both highly uncertain phenomena. But a good combination of technology development strategy and climate

stabilization policy would be highly beneficial in terms of optimizing the timing and the magnitude of climate change mitigation. Obtaining high quality information on both fronts and developing sophisticated analytic tools are crucial for effective R&D strategy. This paper is an attempt to move progress on this issue forward by one more step. From this analysis we learned that the likely contributions of this line of research are to provide insights into the balance of current and future R&D budgets, and to reveal the technologies best suited for the wait-and-see strategy. Extensions of the analysis could help making better-informed decisions for technology development under uncertainties regarding the extent of climate change damage and successful technology development.

Chapter 5. Synthesis and Conclusion

5.1. Contextual Summary of the Three Essays

Climate change is one of the greatest challenges facing humanity. If not effectively mitigated and adapted to, the future generations would suffer the unnecessarily severe damages. Technology is one critical pillar of climate change mitigation. Mitigation of climate change through a reduction in CO_2 emissions would require the energy system to shift away from the conventional use of fossil fuels, but such a shift may impose a high cost on society. Advancements in alternative energy technologies could alleviate the economic burden of this shift by reducing the cost of CO_2 abatement.

This dissertation examines the role that technology plays in mitigating climate change. The three essays contained in this dissertation each focus on different aspect of the process in which advancements in low-carbon energy technologies impact the cost of carbon dioxide (CO_2) abatement. The three essays collectively serve to demonstrate the importance of clearly understanding the differences among low-carbon technologies. They also provide the methodological foundations upon which such technologies can be assessed and compared. Combining these methods with an enhanced understanding of the technologies will contribute to the body of research aimed at minimizing the cost of mitigating climate change. In conjunction with impacts research and adaptation research, this mitigation research can help design an effective climate change policy. This chapter reviews the major insights gained from each of the three essays and discusses their contribution in a broader technology and climate change policy context.

5.1.1. Marginal Cost of Abatement

The first essay focused on the extent to which different individual technologies affect the cost of abatement differently. By building a simple analytical model of energy technologies and CO_2 emissions, I derived sets of conditions under which different types of advanced technologies can be evaluated for their respective strengths in reducing abatement costs at alternate levels of abatement. This exercise is a step forward from the conventional analysis of a single point estimation of the impact of a technology, and it clearly demonstrates the importance of understanding the pattern of abatement cost reductions throughout the potential level of abatement. The conclusions were simple: some technologies are stronger in achieving low levels of abatement, while others are stronger in high levels of abatement. This essay also clearly outlined the conditions that induce such differences and established the basic analytical groundwork for interpreting the numerical analysis examples in the last part of the essay as well as the other analyses contained in the subsequent chapters.

The numerical examples reiterated the findings of the analytical model, demonstrating that the impact of technological change on marginal abatement cost is not uniform across abatement levels; it depends on the characteristics of a particular technology. Different types of technological changes show distinct patterns of the impact on the cost curve, with relative strengths and weaknesses under different abatement levels. The examples also emphasized that merely analyzing either the aggregate marginal abatement cost or the reduction in the cost of energy production cannot provide sufficiently nuanced understanding of the value of technology under emission constraints.

The dynamic interactions in the market matter. It is important to look at the characteristics of each technology to fully explain the interactions and resulting equilibrium.

The relevant characteristics include the magnitude of the reduction in the cost of energy production, the size of the resource base, the rate at which the marginal cost of production increases with scale, and the limiting factor of deployment expansion – such as intermittency of the resource for solar or social opposition to the expansion of nuclear power. In the best case example, a substantial cost reduction in a technology with large resource base or a relaxation of expansion constraints in a low-cost technology could induce a large reduction in the cost of abatement over a wide range of abatement levels. Furthermore, the magnitude of the reduction would be amplified if other low-carbon energy sources are near their respective capacity limits, beyond which the production cost rises rapidly due to the additional efforts required to extract inferior quality resources.

If the socially optimal level of abatement is known, an effective strategy of technology development would be to focus on technologies that exhibit highest strength at the given level of abatement. For the low levels of abatement, the most effective ones could be cost reduction technologies for existing technologies (such as Light Water Reactors). On the other hand, for the high levels of abatement, the most effective ones could be novel technologies that could utilize the existing large resource base (such as Carbon Capture and Storage). The R&D portfolio focusing on the most effective technologies for the chosen abatement level could help minimize the abatement cost under constrained R&D budget.

5.1.2. Technology Interactions

As an extension of the first essay, the second essay focused on how technology *interactions* in the market affect abatement cost. For this analysis, I first built a dataset of abatement costs and energy consumption for the 768 combinations of technology levels and CO_2 stabilization levels. Two or more levels of technology development were obtained from Clarke et al. (2008) for each of the four major supply technologies (solar, wind, nuclear, and carbon capture and storage) and three major end-use efficiency technologies (buildings, industry, and transportation). The final dataset was generated by processing all permutations of the technology levels at two stabilization targets: 450 ppmv and 550 ppmv.

This dataset was then analyzed from three different perspectives: (1) a broad assessment of the degree of variation in the energy consumption and stabilization costs across all the scenarios in the dataset, to highlight general characteristics of the technology space; (2) an assessment of the ranges of stabilization costs associated with each technology development level, which provided insights into issues of risk management; and (3) an assessment of the *reduction* in stabilization cost associated with improvements in individual technologies, which provided information for optimal R&D portfolio analysis.

The insights from the analyses are in agreement with those of the representative scenario analyses upon which they are based. Technological advancements have a substantial impact on stabilization costs, and the impact is larger under more stringent conditions such as a lower stabilization targets or the lack of advancements in other technologies. Improvements in a few particular technologies, most notably CCS, have a

larger impact on stabilization costs than improvements in others. More generally, removing the quantity constraint from a technology, and hence increasing the diversity of available technologies in the market, has a larger impact on stabilization costs than incremental reductions in the production costs of existing technologies.

This effect is best exemplified by the comparison of the two different types of advancements considered for nuclear technology. Consider one type of advancement that allows expansion of nuclear power beyond the current levels of deployment – this could be a technology that minimizes the radioactive waste or one that removes the security threat arising from mismanagement of spent fuel. Even without reduction in production cost, this advancement would allow larger deployment with respect to abatement level, and hence become increasingly effective in reducing stabilization costs under stringent targets. In contrast, the other type of advancement that merely lowers the capital cost below the current level is shown to have relatively smaller reduction potential in stabilization costs, especially for stringent targets.

Furthermore, the analysis also provided more clarity regarding insights not easily demonstrated through representative scenario analyses. One immediate result in this regard was the clear differences in the distribution of the stabilization cost reduction potential between supply technologies and end-use technologies. Generally speaking, advanced supply technologies have their strengths in truncating the high-cost tail of the stabilization cost distribution, which arises with otherwise pessimistic technology outcomes in conjunction with more aggressive climate targets. The flipside is that individual supply technologies yield low value under more relaxed climate targets and under technology-rich conditions, in large part because the advanced supply technologies

are close substitutes of one another. In the presence of multiple advanced supply technologies that can provide sufficient energy at low cost, the value of one additional advanced technology is significantly diminished. On the other hand, advanced end-use technologies are shown to yield relatively consistent value across the full space, in part because they are by their nature contained in a particular sector.

The analysis emphasizes how understanding the interactions between these technologies and their impacts on the cost of abatement can help better inform energy policy decisions, suggesting that an evaluation of R&D investments in an advanced technology should correspond to the policy goal one is trying to achieve. For example, if minimizing the chance of very high stabilization costs is the major goal, one should place additional weight on the supply technologies with high-cost truncation potential. In contrast, if a stable return to R&D investment is the goal, more weight should be placed on aggregate end-use efficiency improvements, compared to the value the conventional representative scenario analysis would suggest.

The dataset and its extensions are of value to the climate change mitigation research community because they provide a rich set of information upon which various uncertainty analyses can be performed. A scenario discovery analysis using the dataset with a goal of identifying technology combinations that are crucial in avoiding high stabilization costs is briefly discussed in the essay. Also, an expanded dataset is under development to be used in an analysis comparing the relative importance of different uncertainties of the climate change problem.

5.1.3. R&D Investment Strategy

The dataset of technology combinations and their impacts on the cost of abatement can be combined with probability of technology success data to generate optimal R&D portfolios under uncertainty. The third essay in this dissertation is one demonstration of such an exercise. In this essay, I took an expanded technology combination dataset, and collected the data points that were compatible with the probabilities of technology success data obtained from the expert elicitations conducted by Baker et al. (2008c, 2009a, 2009b, 2010). The two compatible datasets were integrated into a stochastic dynamic programming framework to generate an optimal R&D portfolio that minimizes the expected cost of abatement given an R&D budget constraint. This analysis identified which technologies should be given R&D funding priorities in order to achieve an atmospheric CO_2 stabilization target at the lowest cost. A multi-period extension of the model allowed intertemporal dynamic optimization where the policy-maker can select the technologies to be invested in immediately as well as the technologies to be invested in later. The analysis emphasized the benefit of having a wait-and-see option that lets the policy-maker further optimize upon the observation of successes and failures of prior investments.

The overall results pointed to R&D portfolios that are diversified across considered technology groups, with a relatively strong emphasis on CCS. However, the technologies considered in this initial analysis may be too limited to be used immediately for policy recommendations. Rather, it is the enhanced understanding obtained from these analyses of the technology space, and the technology interactions within this space that provide more valuable insights.

First of all, the comparison of rank-orders of the technology R&D investment options between the stochastic dynamic programming model and other back-of-the-envelope metrics indicates that a simple product of the probability of success and the maximum abatement cost reduction potential works reasonably well as a rule-of-thumb for ranking the technology R&D priorities. The relative strengths of considered technologies are vastly different, such that no reasonable method of ranking them would substantially alter the order. If plausible, a simple product of the probability of success and the *average impact* would work better. However, this assumes knowledge of the distribution of the potential impact, in which case there is no reason to forego the full stochastic analysis.

A more careful look into the results reveals the subtle differences between an ordering derived by a formal stochastic dynamic programming model and one derived by a simple back-of-the-envelope calculation– such as a simple product of the probability of success and the maximum abatement cost reduction potential of an advanced technology. One immediate difference is the upward movement of end-use technologies in their rankings. This observation is consistent with the results from the second essay that showed that the maximum abatement cost reduction potential metric systematically underestimates the strengths of end-use technologies. The maximum abatement cost reduction potential – often measured by the difference between a baseline scenario and a scenario with one advanced technology – is a commonly used, simple metric in technology evaluation. This result should serves as a caution for such practice in R&D portfolio development.

Furthermore, the results point to a R&D investment strategy of concentrating funds within a homogeneous technology group and diversifying funds across heterogeneous technology groups. Here, a homogeneous technology group is defined by shared resource base and shared applications – for example, the PV technology group that includes many different types of organic and inorganic PV technologies, all of which produce electricity using solar radiation. Different technology groups are defined to be heterogeneous, if the two groups use different resources or have different applications – for example, the PV technology group is categorized to be heterogeneous from the electric vehicle technology group.

Intuitively, multiple successes in a homogeneous technology group result in the inferior technology being effectively wasted. Within a homogeneous technology group, this effect leads to a concentration of funding in the most promising technology to avoid such multiple successes. At the same time, this effect makes lower ranking technology within a group relatively vulnerable to a wait-and-see strategy, where the decision maker observes the progress of a higher-ranking technology before investing in the lower-ranking technology in the same group. This wait-and-see strategy is designed to avoid a situation where both of the technologies succeed and the investment in the inferior technology effectively provides no additional benefit. This relative vulnerability to the wait-and-see strategy leads to a diversification of the R&D portfolio across heterogeneous technology groups. Although the differences observed from these strategies are small, these insights are the additional value provided by conducting a formal analysis of the stochastic technology space.

5.2. Other Aspects of the Policy Process

Throughout the dissertation I have reduced the R&D process to a simple input-output process, as if it were a stochastic vending machine. That is, the R&D funding goes in at one end and advanced technology comes out from the other with a fixed probability, and the policy maker decides which button to press solely to minimize the cost. Given the limitations of this simplification, how widely applicable are these insights in different policy settings? Three aspects of policy process could shed light on this issue.

The first aspect is the nature of the technology R&D process itself. From the most top-down perspective this process may appear like a vending machine, but upon closer examination, it would be more accurately described as a living creature with its own – and sometimes conflicting – objectives. For one thing, technology research labs interact with one another, resulting in a spillover and cross-fertilization across different technologies. These effects would be more prevalent among the research labs specializing in the same type of technology, but certain fields of research – such as basic materials science – may influence many heterogeneous technologies. On the other hand, the spillover effects could be weakened by patents and other intellectual property protection measures, particularly among the private research firms. If such effects are sufficiently strong, an optimal strategy could be to actively form clusters of research to benefit from the effect. This would serve as an opposing force to the "concentration within a homogeneous group" strategy. Future research into the spillover effect either through expert elicitations or through empirical research into the history of technology development could provide valuable information to be used in further refining the R&D portfolio.

There is also the path-dependence aspect in the R&D policy process. An optimal R&D portfolio that minimizes the expected cost of abatement for a given stabilization target may call for a concentration of funding into the most promising technology, while utilizing a wait-and-see strategy for other technologies in the same group. However, upon the initial failure of the first-funded technology, switching to the next promising technology may not be as simple as pressing another button. Once a research apparatus has been established and operated for many years, the natural tendency for it to grow larger and larger. This may happen in the form of formal industry group lobbying or in the form of biased influence toward a policy making individuals. The end result may not be as optimal as what the "vending machine" model has designed for the R&D portfolio solution. The path-dependence effects, if predicted to have substantial impact on the policy, could be added to the model to better represent the suboptimal behavior of the system.

The second aspect of the R&D process to consider is the infrastructure the technologies operate within. The analyses in this dissertation assumed a successfully developed technology is automatically deployed in the energy market on a large-scale, but this is a simplistic abstraction of reality. For one thing, a large-scale deployment in the market generally requires a co-evolution of the infrastructure that supports the new technology. Consider the mass-deployment of personal electric vehicles. This would require a high-voltage charging system to be deployed in a large share of residential buildings, and also possibly in commercial buildings. The electricity supply mix in the grid may need to be adjusted to supply the nighttime charging demand. Furthermore, evolution in the infrastructure may further enhance the attractiveness of the technology.

For instance, if houses were equipped with a smart-metering system, such that an electric vehicle could be charged during the low-demand hours and the peak-demand hours could be supplemented with the batteries, this could reduce the lifetime net ownership cost of the vehicle.

The infrastructure sector has its own policy decisions to make, and such decisions may result in the success or the failure, contingent upon the outcome of the energy technology R&D. Under a stringent climate target that requires advanced energy technologies to be deployed as soon as they become available, it may be necessary for the infrastructure sector to preemptively establish the necessary infrastructure for the rapid deployment of the impending advanced energy technology. But such preemptive action risks cascading failure from the failure of the technology development to the wasted resources in the infrastructure development. To minimize such risk, the infrastructure development could focus on the flexible part of the structure that could be useful either under success or failure, for the reasons similar to the consistent benefit provided by the end-use efficiency technologies. Furthermore, active coordination between the energy technology R&D policy and the infrastructure development policy could maximize the benefit of advanced technology developments.

Future research explicitly representing the co-evolution of the infrastructure the technologies operate within may reveal additional dynamics not observed from the simple "vending machine" treatment I've used. More comprehensive estimates of the broader social cost of abatement could be provided by explicit accounting of additional costs and benefits to consumers and firms associated with the infrastructure – e.g. the establishment of infrastructure, the impeded deployment of new technology due to

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delayed infrastructure, and the infrastructure made obsolete due to the failure in the co-evolution of the energy sector.

The last aspect of the R&D process to consider is the perspective of the policy maker. While the analyses in this dissertation assumed a single global policy optimizer with the sole objective of minimizing the abatement cost, the empirical policy recommendation requires to be evaluated from the perspective of a specific policy maker. Consider the U.S. Department of Energy (DOE), for example. Being a major player in the world energy R&D field, the interests of the DOE may be the most closely aligned with the idealized one-world policy maker perspective used throughout this dissertation. The technologies that minimize the abatement cost for the world are generally the same ones that minimize the costs for the U.S. However, the proportion of benefit generated by the advanced technologies could diminish over time. This may push the R&D portfolio toward a focus on more immediate benefits, when compared to the one-world case. The opposite could be true for a rapidly growing economy such as China. Furthermore, with other major players in the field, it may be strategically beneficial for the U.S. to either compete for dominance in a particular technology group or to collaborate to minimize redundant R&D expenditures. An extension of this analysis using game theory could shed more light on the issue.

The domestic climate policy structure is also important to the perspective of the DOE. Throughout this dissertation, I have assumed an idealized global carbon market that optimally equalizes the carbon price of all countries and of all sectors. However, since the international community has so far failed to agree on a comprehensive successor to the Kyoto Protocol, it is likely that such an idealized market will not be

established in the near future. Instead, the near-future climate policy will likely be dominated by a multitude of region-specific and sector-specific policies that are prone to price distortions and emissions leakage.

If such suboptimal climate policies are applied for a prolonged period of time, the R&D portfolio may also diverge from the globally optimal case. Assuming the long-term climate target remains the same, the relative importance of the technologies is unlikely to change dramatically. However, among the similar-strength technologies, more immediate focus may be given to the end-use technologies. As observed throughout the analyses, end-use efficiency technologies show relatively consistent performance under different situations. The suboptimal policy environment would be no exception. An increase in end-use efficiency would shrink the size of the pie that the energy supply technologies must fill. The impacts would be two-fold: one, this would reduce emissions during the suboptimal policy regime by reducing the amount of energy consumed, and two, this would set the stage for the future advanced low-carbon supply technologies to more rapidly saturate the energy system once the optimal climate policy comes into effect.

In contrast, an early development of an advanced CCS technology would sit idle during the suboptimal policy regime, until the start of more aggressive climate policy. This dynamic would be more pronounced if the future prospect of the optimal climate policy itself is uncertain, and there is a significant chance that such climate policy will never be established. In such a case, advanced CCS may never be utilized on a large scale. Overall, the prospect of a prolonged suboptimal policy regime would push the R&D portfolio toward an "end-use efficiency now, supply technology later" design.

On the opposite spectrum of the climate policy regime is the sub-2°C target. For years, scientific discourse centered around the 2°C target, roughly corresponding to the 450 ppmv case in my analyses. Recently, there have been more discussions about the climate target below the benchmark 2°C. If the climate science research supports a climate target as low as 1.5°C or even 1°C in the long run, it could change the optimal R&D portfolio. Such stringent targets would likely require a portfolio beyond the conventional energy R&D portfolio, and would likely include technologies to control other greenhouse gases and climate forcing agents as well as active scrubbing of CO_2 from the atmosphere. Since CO_2 has an atmospheric lifetime of a century or so, even with a rapid phase-out of fossil fuels, the previously emitted CO_2 will stay in the atmosphere and continue to warm the Earth. Reversing the warming trend early enough to avoid overshooting a sub-2°C target would require reductions in all applicable greenhouse gases. In order to have immediate reduction in the rate of warming until the effect of CO_2 reduction starts to prevail, it would be particularly effective to reduce the short-lived and highly-potent greenhouse gases and forcing agents, such as methane and black carbon. Furthermore, achieving a very low climate target within a short time frame may require aggressive utilization of negative emission technologies that can scrub CO_2 or other greenhouse gases from the atmosphere. Thus, investments in the technologies for abatements in the other greenhouse gases and forcing agents and for active scrubbing of the gases should be considered alongside with the advanced low-carbon energy technologies.

Within the energy sector, low climate targets would push the optimal R&D portfolio further toward the one technology that could produce carbon-negative energy: a

biomass-fired powerplant with CCS. Among other energy technologies, an extrapolation of the changes from 550 ppmv to 450 ppmv indicates that the change in priority ranking would not be too dramatic, but technologies that allow decarbonization of the transportation sector would also receive additional favor. This is because, with the set of technologies that are currently available, the transportation sector is the most difficult to decarbonize. A very low climate target would require decarbonization of all sectors, along with the implementation of carbon-negative technologies in the sectors that are capable. A technology that could ease the transition of the transportation sector away from liquid hydrocarbon fuel would be highly beneficial under these stringent targets.

5.3. Critical Assumptions and Sensitivities

Finally, the sensitivities of the conclusions merit discussion. Before discussing the list of sensitivities, it must be reiterated that the analyses included in this dissertation are primarily geared toward a demonstration of the stochastic modeling capability to generate an optimal R&D portfolio; the specific composition of the generated portfolio is the secondary outcome of the exercise. Beyond that, of course, the findings do point towards general insights for technology dynamics and climate change policy design.

Development of an optimal technology R&D portfolio is based on a specific set of assumptions that are taken to be exogenous. Therefore, the specific composition of the portfolio hinges on the critical assumptions discussed below, and should be treated with caution.

First, the analysis takes the expert elicitation results as given. Ideally, the selected groups of experts should present impartial judgments about the future prospects of the

technologies, and the elicitation results should closely reflect the true probability of success. However, the elicitation process could be distorted by several factors, including unfamiliarity with the cost metrics, overconfidence, shared bias among experts, missing observations, and so on. Some elicitation data used in this dissertation are originally obtained from as many as seven experts, such that the impact of one imprecise measurement on the overall results would be dampened by the averaging process. However, some early experimental elicitations data are based on as few as three experts, in which case one imprecise measurement could dramatically change the resulting portfolio. The effect of biased estimates on the average value decreases by half for every doubling of experts. For example, suppose the true value is 0.2. If one expert was doubly overconfident at 0.4 and all others were symmetrically distributed around the true value, the average value would be 0.3 for three experts – an overall overestimation of 33%. For six experts, the average value would be 0.23 – an overall overestimation of 17%. It is not until the number of experts reaches 20, the averaged bias is reduced below 5%. The number of experts necessary to contain the effect of a bias within a fixed margin linearly increases with respect to the magnitude of the bias. Considering the small number of experts elicited for the probabilities data used here, the analyses contained in this dissertation should be treated as "what if" exercises where the elicitations had been the best available data.

Expert elicitation, and more generally a probability estimation approach to the future prospects of R&D, is a relatively new addition to the field of low-carbon energy research. A few large-scale expert elicitation projects are currently under way, and further

refined data obtained from these exercises could provide valuable data upon which the stochastic analysis can be performed to generate new sets of optimal R&D portfolios.

Second, the analysis uses a stochastic approach to the four technology groups considered, but a deterministic approach to every other parameter. The analysis hinges on a deterministic *baseline* scenario developed by the GCAM development team for the report submitted to the Climate Change Technology Program. While GCAM is one of the most widely used models in the field, and its baseline scenario is the result of rigorous research and cross-validation, it is still subject to the same risk of imprecise measurement as the expert elicitations process. While the independent review process for the development of GCAM's baseline scenario may reduce the magnitude of any bias, the effect of a biased parameter in the baseline scenario could be exacerbated in the analyses, because the impacts of the technological changes are measured relative to this single deterministic baseline.

There are two possible ways in which an imprecise representation in the baseline could affect the outcome. One case is consistently optimistic or pessimistic assumptions across all of the technologies considered. In such a case, all impacts of technological changes would be biased in the same direction, and would have minimal impact on the final composition of the portfolio. On the other hand, it could be the case that the baseline scenario could be optimistic for a specific technology, but pessimistic for other technologies. Consider the recent experience with high nuclear capital costs and low natural gas costs. From the perspective of a long-run equilibrium model like GCAM, price spikes at the length of a few years are merely temporary fluctuations that will eventually converge toward a long-run equilibrium. However, if future trends prove that

this recent experience is indeed a permanent one, an analysis with a revised baseline reflecting the change may result in a different portfolio solution. This solution may place a stronger emphasis on the gas powerplant CCS technologies, as well as a specific type of nuclear reactor technology that could effectively offset the main culprit of the high capital cost – be it added passive safety measures, environmental regulations, unexpected delays in licensing, and so on. A stochastic approach to the baseline assumptions could be used in future analyses in order to moderate the impact of biased baseline parameters.

Third, the analysis uses particular representations of uncertainty resolution and delayed technology development. To make the analysis transparent, tractable, and computationally manageable, the time-dimension of the stochastic optimization problem has been reduced to two decision periods along with the final uncertainty resolution period. The two decision periods are the minimum number needed to capture the dynamics associated with the wait-and-see strategy. While there is a case to be made that the second decision period conceptually represents a normalized aggregation of all the future decision periods that follow, there may be some unforeseen dynamics that could be missed by this minimal number of decision periods. Generally speaking, each additional decision period will further enforce the wait-and-see strategy, and the diversified portfolio that results from it.

In addition, the uncertainty of technology success is assumed to be fully resolved within the 10-year gap between the first and the second decision periods. This is a rather simplistic abstraction of the real-world R&D process, where the decisions may be continuously updated upon partial resolution of technology uncertainty. Computational resources permitting, it would be a valuable extension of the model to explicitly represent

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a partial resolution of technology uncertainty. Considering the minimal difference observed between the first period portfolio of the dynamic model and the portfolio resulting from the single-period model – which effectively represents the other extreme case of a zero uncertainty resolution, it would be unlikely that the partial-resolution model would yield a first period portfolio that is substantially different from the two cases. We could conjecture that the partial resolution model solution would lie somewhere between the two models presented here.

However, if combined with a more refined representation of the "learning from failure" effect, the partial resolution model could show additional dynamics not observed from the two extreme cases of the model. For instance, if there are clear differences in the speed and the level of uncertainty resolution among technologies, there may be additional dynamics utilizing the value of information that pushes the first period portfolio toward the technologies that provide better uncertainty resolution, such that the problem of overlapping multiple successes in the same group could be reduced.

Considering the simplifying assumptions made in the model, the insights gained from the analysis may need to be utilized in a less restrictive form in the practical applications where the decision periods are continuous and the uncertainty resolution is not instantaneous. The "diversify across and concentrate within" strategy deduced from the abstract model would in practice mean focusing on a smaller subset of technologies in a homogeneous group, while broadly covering the range of heterogeneous technology groups. This insight would be practically useful if facing a decision on whether to fund an otherwise inferior technology when there exists a technology with superior performance

with high probability of success, which could potentially make the inferior technology obsolete upon successful development.

Related to the intertemporal dynamics, the sensitivity to the discount rate should also be noted. Throughout the dissertation a single real discount rate of 5% is used. The choice of discount rate affects both the benefit of wait-and-see in the form of interest accumulation, as well as the cost of wait-and-see in the form of delayed impact on the abatement cost. The impact of a high or low discount rate across technologies would be in the same direction, and the relative magnitude is unlikely to be substantially different. All considered technologies show incremental improvement in the baseline case and rapid improvement early on in the advanced case. The shared shape of the intertemporal technology development trajectory would lead to a shared direction and relative magnitude of impact associated with the discount rate choice. Considering the robustness of the R&D rank-order observed across different models and constraints, the choice of a different discount rate is unlikely to make a substantial difference in an optimal R&D portfolio choice among the considered technologies.

In contrast, what is likely to be highly sensitive to the choice of discount rate is the share of the current and future R&D budget. Consider the extremes. A zero discount rate would push most of the R&D investment toward the first investment periods; only the most extreme wait-and-see strategy would sacrifice the first few years of abatement cost reduction in order to gain from the uncertainty resolution. On the other hand, a high discount rate would likely push the budget toward the second period. A high enough discount rate could allow for the saving of one unit investment in the first period in exchange for two or more units of investment in the second period. The magnitude of the

benefit of such an exchange would be partially offset by the potential loss in abatement costs in the early periods, which now constitute a larger proportion of the total net present value of the abatement cost due to the same high discount rate. The combined effect would be a moderate change toward a larger share of total budget for the future period.

All these sensitivities to critical assumptions collectively reiterate caution on using research based on narrow ranges of assumptions for immediate policy action. While using the stochastic approach to the technology space is a step forward from the conventional deterministic scenario analysis, other uncertain aspects of the model have not been subject to the same level of rigor in this dissertation. These other sensitivities should serve as a guidance for future improvement of the model. Any immediately actionable R&D policy recommendations should be robust across reasonable ranges of the assumptions.

There are several general insights distilled from the analyses that are likely robust across the various assumptions. One robust insight is the R&D investment strategy of concentrating funds within a technology group with homogeneous applications and diversifying funds across heterogeneous technology groups. The degree to which this strategy affects the final R&D portfolio may change with respect to discount rate or the way uncertainty resolution is formulated. However, this strategy remains a useful guideline for R&D portfolio design, as it helps minimize the loss due to multiple successes within the same technology group.

Another robust observation is the relatively narrow variance in end-use efficiency technologies. This effect led to a systematic underestimation of their strength in the commonly used metric of maximum abatement cost reduction potential. Explicitly

considering probabilities of multiple technology successes provides a balanced

perspective for both supply technologies and the end-use technologies.

5.4. Synthesis

This dissertation includes three essays, each attempting to further advance understanding

of the technology space in the context of climate change mitigation. Collectively, they

form a sequential set of research, where the analytical foundation is first developed for

understanding how low-carbon energy technologies induce differential impacts on the

abatement cost, the dataset of the full technology combinations is built and analyzed to

enhance the understanding of the technology interactions, and a stochastic optimization

model is applied to the dataset to generate an optimal R&D portfolio under uncertainty.

Each step in this line of research adds one more dimension in analyzing the impact of

technology on the mitigation cost. Considering the limited scope of the research and the

sensitivities to the critical assumptions, several additional refining studies will be needed

before this line of research can produce an immediately applicable R&D portfolio.

However, it is the incrementally richer understanding gained from each step taken in the

three essays that provides the value-added to the field. The richer the understanding of

the technology dynamics for climate change mitigation, the stronger the foundation upon

which the next stage of research can be conducted.

Appendix 1: Total abatement cost with delayed technology development (in trillions of 2005 constant dollars).

(A) 450 ppmv target

			Transportation								
			TRNr0	TRNa0	TRNa1	TRNb0	TRNb1	TRNc0	TRNc1	TRNd0	TRNd1
NUCr0	SOLr0	CCSr0	12.27	11.90	11.98	11.66	11.78	11.75	11.85	11.25	11.50
		CCSa0	11.15	10.79	10.87	10.57	10.68	10.65	10.75	10.16	10.40
		CCSa1	11.33	10.97	11.04	10.74	10.85	10.82	10.92	10.33	10.57
		CCSb0	10.25	9.90	9.98	9.67	9.78	9.75	9.85	9.28	9.50
		CCSb1	10.64	10.28	10.36	10.05	10.16	10.13	10.23	9.65	9.88
		CCSc0	9.51	9.16	9.24	8.93	9.04	9.02	9.11	8.54	8.77
		CCSc1	10.00	9.64	9.72	9.42	9.53	9.50	9.60	9.02	9.25
	SOLa0	CCSr0	11.87	11.50	11.59	11.26	11.38	11.35	11.46	10.87	11.10
		CCSa0	10.90	10.53	10.62	10.30	10.42	10.38	10.49	9.90	10.14
		CCSa1	11.05	10.69	10.77	10.46	10.57	10.54	10.64	10.05	10.29
		CCSb0	10.07	9.71	9.79	9.48	9.60	9.57	9.67	9.08	9.32
		CCSb1	10.40	10.04	10.13	9.82	9.93	9.90	10.00	9.42	9.66
		CCSc0	9.37	9.02	9.10	8.79	8.90	8.87	8.97	8.39	8.63
		CCSc1	9.80	9.45	9.53	9.22	9.33	9.30	9.40	8.82	9.05
	SOLa1	CCSr0	12.04	11.68	11.76	11.44	11.56	11.52	11.63	11.03	11.27
		CCSa0	11.04	10.67	10.75	10.44	10.56	10.52	10.62	10.03	10.27
		CCSa1	11.20	10.83	10.91	10.60	10.72	10.69	10.79	10.19	10.43
		CCSb0	10.18	9.82	9.91	9.59	9.71	9.68	9.78	9.19	9.43
		CCSb1	10.54	10.18	10.26	9.94	10.06	10.03	10.13	9.54	9.78
		CCSc0	9.46	9.11	9.18	8.88	8.99	8.96	9.06	8.48	8.71
		CCSc1	9.92	9.56	9.64	9.33	9.45	9.42	9.52	8.93	9.17

	SOLr0	CCSr0	9.73	9.41	9.48	9.20	9.32	9.28	9.38	8.85	9.07
		CCSa0	9.07	8.75	8.83	8.56	8.66	8.63	8.72	8.21	8.41
		CCSa1	9.20	8.89	8.96	8.69	8.78	8.76	8.85	8.34	8.54
		CCSb0	8.53	8.23	8.29	8.03	8.12	8.10	8.19	7.67	7.88
		CCSb1	8.82	8.51	8.58	8.31	8.41	8.39	8.47	7.96	8.17
		CCSc0	8.05	7.74	7.80	7.53	7.63	7.61	7.69	7.18	7.39
		CCSc1	8.43	8.12	8.20	7.92	8.02	7.99	8.08	7.57	7.77
NUCb0	SOLa0	CCSr0	9.53	9.21	9.28	9.01	9.11	9.08	9.17	8.64	8.86
		CCSa0	8.92	8.61	8.68	8.40	8.50	8.47	8.56	8.04	8.26
		CCSa1	9.04	8.73	8.80	8.52	8.62	8.60	8.69	8.16	8.37
		CCSb0	8.42	8.11	8.18	7.91	8.01	7.98	8.07	7.55	7.76
		CCSb1	8.68	8.37	8.44	8.17	8.27	8.24	8.33	7.81	8.02
		CCSc0	7.96	7.65	7.72	7.45	7.55	7.52	7.60	7.09	7.29
		CCSc1	8.32	8.00	8.07	7.80	7.90	7.88	7.97	7.44	7.65
	SOLa1	CCSr0	9.64	9.32	9.39	9.11	9.22	9.18	9.28	8.74	8.97
		CCSa0	9.01	8.70	8.77	8.49	8.60	8.57	8.66	8.14	8.35
		CCSa1	9.14	8.83	8.90	8.62	8.73	8.69	8.79	8.26	8.47
		CCSb0	8.50	8.20	8.26	7.99	8.09	8.07	8.15	7.63	7.84
		CCSb1	8.78	8.47	8.54	8.26	8.36	8.34	8.43	7.91	8.11
		CCSc0	8.04	7.72	7.79	7.52	7.62	7.59	7.68	7.16	7.37
		CCSc1	8.40	8.10	8.16	7.89	7.99	7.96	8.05	7.53	7.73
	SOLr0	CCSr0	10.37	10.04	10.12	9.83	9.94	9.90	10.00	9.47	9.70
		CCSa0	9.55	9.24	9.31	9.03	9.14	9.11	9.20	8.68	8.89
		CCSa1	9.71	9.38	9.47	9.18	9.29	9.25	9.36	8.82	9.04
		CCSb0	8.94	8.63	8.70	8.42	8.53	8.50	8.59	8.07	8.28
		CCSb1	9.27	8.94	9.02	8.74	8.85	8.82	8.91	8.38	8.59
		CCSc0	8.40	8.08	8.15	7.88	7.98	7.95	8.04	7.52	7.73
		CCSc1	8.82	8.51	8.58	8.30	8.40	8.37	8.47	7.94	8.16
NUCb1	SOLa0	CCSr0	10.10	9.77	9.86	9.57	9.68	9.64	9.74	9.21	9.43
		CCSa0	9.37	9.05	9.12	8.84	8.95	8.92	9.01	8.49	8.70
		CCSa1	9.51	9.18	9.26	8.98	9.09	9.05	9.15	8.61	8.83
		CCSb0	8.81	8.48	8.56	8.28	8.38	8.35	8.45	7.92	8.13
		CCSb1	9.09	8.77	8.85	8.56	8.67	8.64	8.74	8.20	8.42
		CCSc0	8.29	7.98	8.05	7.77	7.87	7.84	7.93	7.40	7.62
		CCSc1	8.68	8.36	8.43	8.15	8.25	8.23	8.32	7.79	8.01
	SOLa1	CCSr0	10.24	9.91	9.99	9.70	9.81	9.78	9.88	9.33	9.56
		CCSa0	9.48	9.16	9.23	8.95	9.05	9.02	9.12	8.59	8.80
		CCSa1	9.62	9.30	9.38	9.09	9.20	9.16	9.26	8.63	8.94
		CCSb0	8.90	8.58	8.65	8.37	8.48	8.45	8.54	8.01	8.22
		CCSb1	9.20	8.88	8.95	8.67	8.78	8.74	8.84	8.30	8.52
		CCSc0	8.37	8.05	8.12	7.85	7.95	7.92	8.01	7.48	7.70
		CCSc1	8.78	8.46	8.53	8.25	8.35	8.33	8.42	7.88	8.10

(B) 550 ppmv target

			Transportation								
			TRNr0	TRNa0	TRNa1	TRNb0	TRNb1	TRNc0	TRNc1	TRNd0	TRNd1
NUCr0	SOLr0	CCSr0	2.90	2.78	2.80	2.71	2.73	2.73	2.75	2.57	2.62
		CCSa0	2.70	2.59	2.60	2.51	2.53	2.54	2.56	2.39	2.42
		CCSa1	2.71	2.60	2.61	2.53	2.54	2.55	2.57	2.40	2.43
		CCSb0	2.41	2.30	2.31	2.23	2.25	2.26	2.27	2.11	2.14
		CCSb1	2.46	2.35	2.37	2.28	2.30	2.31	2.32	2.16	2.19
		CCSc0	2.16	2.05	2.06	1.99	2.00	2.01	2.02	1.87	1.90
		CCSc1	2.24	2.13	2.14	2.06	2.08	2.09	2.10	1.94	1.97
	SOLa0	CCSr0	2.66	2.54	2.56	2.47	2.49	2.50	2.52	2.35	2.38
		CCSa0	2.49	2.38	2.39	2.31	2.33	2.33	2.35	2.19	2.22
		CCSa1	2.50	2.39	2.40	2.32	2.34	2.34	2.36	2.20	2.23
		CCSb0	2.24	2.13	2.14	2.06	2.08	2.09	2.10	1.95	1.98
		CCSb1	2.28	2.17	2.18	2.10	2.12	2.13	2.14	1.99	2.02
		CCSc0	2.02	1.92	1.93	1.85	1.86	1.87	1.89	1.73	1.76
		CCSc1	2.08	1.98	1.99	1.91	1.93	1.93	1.95	1.79	1.82
	SOLa1	CCSr0	2.71	2.60	2.61	2.52	2.55	2.55	2.57	2.40	2.44
		CCSa0	2.54	2.43	2.44	2.36	2.38	2.38	2.40	2.24	2.27
		CCSa1	2.55	2.44	2.45	2.37	2.39	2.39	2.41	2.24	2.28
		CCSb0	2.29	2.18	2.19	2.11	2.13	2.14	2.15	1.99	2.02
		CCSb1	2.33	2.22	2.24	2.16	2.17	2.18	2.20	2.03	2.07
		CCSc0	2.06	1.96	1.97	1.89	1.91	1.92	1.93	1.77	1.80
		CCSc1	2.13	2.03	2.04	1.96	1.97	1.98	2.00	1.84	1.87

NUCb	SOL	CCS									
NUCb0	SOLr0	CCSr0	2.11	2.01	2.02	1.94	1.96	1.97	1.98	1.83	1.86
		CCSa0	2.02	1.92	1.93	1.85	1.87	1.87	1.89	1.73	1.77
		CCSa1	2.02	1.92	1.94	1.86	1.87	1.88	1.90	1.74	1.77
		CCSb0	1.85	1.76	1.77	1.69	1.71	1.72	1.73	1.58	1.61
		CCSb1	1.89	1.80	1.81	1.73	1.75	1.75	1.77	1.62	1.65
		CCSc0	1.69	1.60	1.61	1.53	1.55	1.56	1.57	1.43	1.45
		CCSc1	1.76	1.66	1.67	1.60	1.61	1.62	1.63	1.49	1.52
	SOLa0	CCSr0	1.98	1.88	1.90	1.82	1.83	1.84	1.85	1.70	1.73
		CCSa0	1.90	1.80	1.81	1.73	1.75	1.76	1.77	1.62	1.65
		CCSa1	1.90	1.80	1.82	1.74	1.76	1.76	1.78	1.63	1.66
		CCSb0	1.75	1.65	1.66	1.59	1.61	1.61	1.63	1.48	1.51
		CCSb1	1.78	1.69	1.70	1.62	1.64	1.65	1.66	1.51	1.54
		CCSc0	1.60	1.51	1.52	1.45	1.46	1.47	1.48	1.34	1.37
		CCSc1	1.66	1.57	1.58	1.50	1.52	1.53	1.54	1.40	1.42
	SOLa1	CCSr0	2.03	1.92	1.94	1.86	1.87	1.88	1.90	1.74	1.77
		CCSa0	1.94	1.84	1.85	1.77	1.79	1.80	1.81	1.66	1.69
		CCSa1	1.94	1.85	1.86	1.78	1.80	1.80	1.82	1.66	1.69
		CCSb0	1.79	1.69	1.70	1.63	1.64	1.65	1.67	1.52	1.55
		CCSb1	1.82	1.73	1.74	1.66	1.68	1.69	1.70	1.55	1.58
		CCSc0	1.64	1.55	1.56	1.48	1.50	1.51	1.52	1.37	1.40
		CCSc1	1.70	1.61	1.62	1.54	1.56	1.57	1.58	1.43	1.46
NUCb1	SOLr0	CCSr0	2.22	2.12	2.13	2.05	2.06	2.07	2.09	1.93	1.96
		CCSa0	2.11	2.01	2.02	1.94	1.96	1.97	1.98	1.83	1.86
		CCSa1	2.12	2.02	2.03	1.95	1.97	1.98	1.99	1.84	1.87
		CCSb0	1.93	1.83	1.84	1.77	1.78	1.79	1.80	1.66	1.69
		CCSb1	1.97	1.88	1.89	1.81	1.83	1.83	1.85	1.70	1.73
		CCSc0	1.75	1.66	1.67	1.60	1.61	1.62	1.63	1.49	1.52
		CCSc1	1.82	1.73	1.74	1.66	1.68	1.69	1.70	1.56	1.58
	SOLa0	CCSr0	2.07	1.97	1.98	1.90	1.92	1.93	1.94	1.79	1.82
		CCSa0	1.97	1.87	1.88	1.81	1.82	1.83	1.85	1.70	1.73
		CCSa1	1.98	1.88	1.89	1.81	1.83	1.84	1.85	1.70	1.73
		CCSb0	1.81	1.71	1.72	1.65	1.67	1.67	1.69	1.54	1.57
		CCSb1	1.85	1.75	1.76	1.69	1.70	1.71	1.72	1.58	1.61
		CCSc0	1.65	1.56	1.57	1.50	1.51	1.52	1.53	1.39	1.42
		CCSc1	1.71	1.62	1.63	1.55	1.57	1.58	1.59	1.45	1.47
	SOLa1	CCSr0	2.11	2.01	2.03	1.95	1.96	1.97	1.99	1.83	1.86
		CCSa0	2.02	1.92	1.93	1.85	1.87	1.88	1.89	1.74	1.77
		CCSa1	2.02	1.92	1.94	1.86	1.87	1.88	1.90	1.75	1.78
		CCSb0	1.85	1.76	1.77	1.69	1.71	1.72	1.73	1.58	1.61
		CCSb1	1.89	1.79	1.81	1.73	1.75	1.75	1.77	1.62	1.65
		CCSc0	1.69	1.60	1.61	1.54	1.55	1.56	1.57	1.43	1.45
		CCSc1	1.75	1.66	1.67	1.60	1.61	1.62	1.63	1.49	1.51

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