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Endogenous Technological Change In The DICE Integrated Assessment Model

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Endogenous Technological Change In The DICE Integrated Assessment Model

A Thesis Presented

by

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DEDICATION

To Bill W.

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ABSTRACT

ENDOGENOUS TECHNOLOGICAL CHANGE IN THE DICE INTEGRATED ASSESSMENT MODEL

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Integrated Assessment Models (IAM)s play a key role in climate policy research; however, many IAMs are limited by their treatment of technological change. This is a particularly vexing limitation because technological change significantly affects the optimal carbon policy. We propose a means of incorporating technological change within the Dynamic Integrated Model of the Climate and Economy (DICE). We modify DICE to allow it to adjust the cost of CO2 abatement based on the demand for solar photovoltaic generating capacity.

We find that deployment of solar photovoltaics (PV) is highly sensitive to returns to scale and the grid integration costs associated with PV intermittency. At low returns to scale integration costs cause PV to be deployed in steps, reducing the benefit of scale effects; at higher returns to scale PV is deployed smoothly but is arrested integration costs become significant; and when returns are high PV becomes so inexpensive that it's deployed widely in spite of integration costs. The implication of this behavior is that the optimal allocation of research and development resources depends on returns to scale in the solar market: if returns to scale are low, R&D should focus on PV itself, while if they're high, R&D should focus on reducing integration costs.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Motivation

Integrated Assessment Models (IAMs) are important tools of climate change policy research, but many IAMs are limited by their treatment of technological change. This is a vexing limitation because any carbon dioxide (CO2) emissions policy will induce technological change, and models which cannot capture this dynamic may miss valuable insights, with costly and possibly counterproductive results.

One common approach to modeling technological change is to use an exogenous parameter known as an autonomous energy efficiency index (AEEI). The AEEI approach has the merit of simplicity, but it cannot model the Induced Technological Change (ITC) caused by a carbon policy. These problems have been recognized as serious limitations for IAMs; consequently there has been a trend towards using endogenous technological change in IAMs.

1.2 Objectives

The goal of this thesis is to implement a framework for endogenous technological change in one well-known IAM and analyze the impact of ITC on the model's predictions. By synthesizing the research about the nature of technological change and its effect on abatement cost we develop an endogenous framework for technological change within the Dynamic Integrated Model of the Climate and Economy (DICE) model, implement a simplified model of the zero carbon energy market within that framework, and analyze the impact of ITC on the optimal level of carbon emissions. For the balance of this thesis we will refer to the unmodified DICE 2007 model as “DICE”, and our modified model as “DICE-S”, for DICE with Scale.

1.3 Contributions

This work contributes to scholarly knowledge by addressing the challenges of incorporating ITC in an IAM, with the objective of building a model capable of exploring technology policy alongside market policy. This is important because models which cannot capture ITC tend to overestimate the true cost of abatement (Popp 2004). While at first glance, the implication of overestimating abatement costs may seem to be a simple cost savings, they’re more complex: a more accurate representation of abatement costs could change the optimal policy. This has important ramifications for society because once a policy has been adopted changing course could be extremely costly or even impossible. This model provides a tool for exploring the complex impact of technological change on optimal carbon policy.

CHAPTER 2

BACKGROUND

2.1 Climate Change From an Economic Perspective

In the popular media climate change is frequently presented in terms of global temperature increases, retreating ice sheets, rising ocean levels, and the dire consequences such events may have for Earth's ecosystem. Economists take a different perspective: they focus on the economic impact of ecological change rather than change itself. This is an important point, and one that is easily misunderstood. The fact that economists aren't directly concerned with the environment does not mean that they are unconcerned: economists recognize that the environment has intrinsic value which is diminished by climate change, but economists also recognize the economic benefits of consuming natural resources; and that such benefits outweigh the costs, up to a point. To the economist, addressing climate change is an optimization problem.

The economy is composed of many agents acting independently in their own self-interest. The interactions between these agents—the market—impose an important constraint on social planning, namely that any effective policy must either be optimal for each individual agent or enforced through costly measures. On the other hand, the perfectly competitive market's remarkable ability to allocate resources efficiently can be harnessed to society's advantage by transforming an intractably complex problem into a more manageable exercise in market regulation. For these reasons, large scale economic problems must be addressed from the perspective of market regulation.

2.1.1 Climate Change as a Market Failure

The primary market imperfection affecting the climate change problem is the externality created by CO2 emissions; since emitters reap all of the benefits of their emissions but only a fraction of the damages, they emit at a sub-optimally high level.

The concept of pollution as a market failure is not new. In the early 20th century Pigou (1932) advanced an argument for taxation as a means of addressing pollution externalities. Later, Coase (1960) argued that property rights can address externalities in certain situations, but also noted that in some cases transaction costs associated with such rights could exceed their value. Hardin (1968) coined the term *tragedy of the commons* to describe a situation in which an externality affecting a nonexcludeable good encourages its depletion. Climate change has long been conceptualized within this framework: William Nordhaus, the creator of DICE, characterized the climate change problem as managing the global commons (Nordhaus 1994) , and more recently climate change has been called the greatest market failure the world has ever seen (Stern 2007).

2.1.2 The Role of Climate Change Policy

The goal of climate change policy is to address the market failures that are the underlying drivers of climate change. The tools to repair market failures can be grouped into two categories. Interventional approaches such as Pigouvian taxation (Pigou 1932), quotas, and Cosian bargaining (Coase 1960) all have the underlying strategy of valuing the externality by means of some market intervention. On the other hand, structural, or technology-based approaches such as R&D attempt to remove the economic incentive to produce the externality.

2.2 Technological Change

Wing (2006) defines technological change as *"a change in the character of productive activity"* and decomposes the drivers of technological change into invention, fueled by creativity and scientific knowledge; innovation, the application of engineering knowledge to scaling up and commercializing existing technologies; and diffusion of the technologies throughout the economy. These stages outline the path taken by new technologies as they are first invented, then commercialized, and finally diffused throughout the economy. While the qualitative relationship between technology and economic output is clear, a quantitative relationship has been elusive, especially for the long time horizon of the climate change problem.

2.2.1 Learning by Doing

The beginnings of endogenous technological change date back more than a century to Bryan, and Harter (1899) (cited in (Nordhaus 2008)), who noted that performance of telegraph operators improved with experience. Hicks (1932), proposed the theory of ITC, whereby cost minimizing motives will incentivize firms to economize on the costliest factors of production. Among the first to notice a relationship between cost and experience in a manufacturing setting was Wright (1936), who noted that the number of hours required to build an aircraft decreased with each unit produced. Later work by Arrow (1962) further developed the concept of learning by doing.

Learning by doing has proven to be a useful metric for many technologies and is now part of the industrial engineering canon. However, as discussed below, using a learning model at higher levels of aggregation may be problematic.

2.2.2 Returns to Scale

Return to scale is the concept that the unit cost of a good decreases as a function of the scale of production. It is structured similarly to the learning curve, except that cumulative production is replaced with a representation of the relative change in capacity from some arbitrary starting point.

2.2.3 Induced Technological Change

Cost minimization implies that increasing prices will spur innovation that economizes on the factors of production. First introduced by Hicks (1932), ITC implies that price instruments will affect the rate of technological change. Over the long term, this can have a significant effect on the optimal portfolio.

Although there is considerable literature which concludes that ITC alone will not be enough to solve climate change (Goulder 2004, de Coninck et al. 2008, Gainza-Carmenates et al. 2010), its self-enforcing nature may have significant implications because mitigation costs rise exponentially in the face of incomplete participation (Keppo, Rao 2007).

2.3 Abatement[1]

In this thesis we follow Baker, Clarke & Shittu (2008) by defining abatement as a reduction in emissions below a baseline, in this case the profit maximizing level in the absence of both technological change and a carbon policy. Abatement will occur whenever either a carbon policy or technological change leads to a new optimum at a lower level of emissions. Abatement is often discussed in terms of the Marginal Abatement Cost (MAC) and Total Abatement Cost (TAC); the TAC is the total cost of achieving a given level of abatement, while the MAC is the cost of abating the next unit of emissions.

2.3.1 The Total Abatement Cost Curve

The TAC curve is defined as the difference between profit or GDP with and without a constraint on emissions, with respect to abatement level (Baker, Barron 2013). This definition is illustrated in Figure 1 below. Panel (a) illustrates the firm's abatement problem: emissions constraints e_i represent all possible combinations of abatement μ and output y and which result in emissions level e_i; the firm's corresponding maximal isoprofit curves π_i are tangent to the constraints at the profit maximizing combination of output and abatement. Note that as the emissions constraint tightens, the optimal point moves up and to the left. This reflects the fact that firms will choose to achieve some abatement through output reduction, rather than through abatement effort alone. Panel (b) illustrates the corresponding TAC curve.

[1] The content of this section borrows heavily from *Technical Change and the Marginal Cost of Abatement*, in the Encyclopedia of Energy, Natural Resource, and Environmental Economics (Baker, Barron 2013).

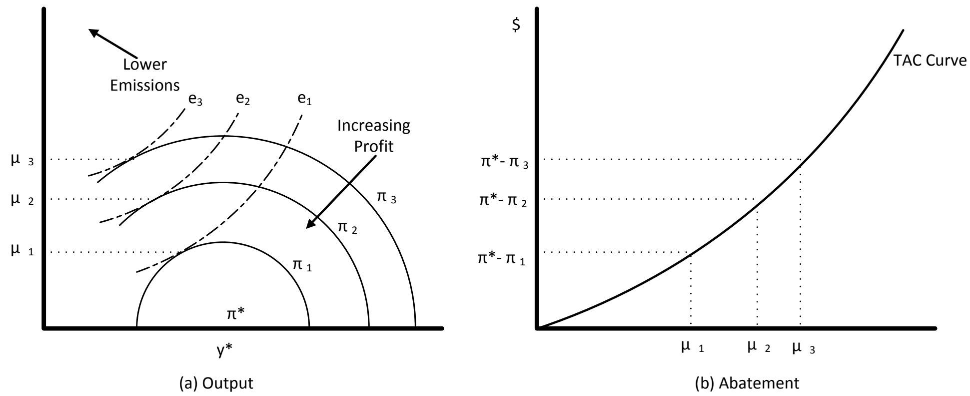

Figure 1: Generating abatement cost curves: (a) The abatement problem, (b) The TAC curve (Adapted from (McKitrick 1999, 306-314)).

2.3.2 The Marginal Abatement Cost Curve

The Marginal Abatement Cost (MAC) curve is obtained by differentiating the TAC with respect to abatement. As shown in Figure 2, it can be used to determine the optimal level of emissions in society, the level of abatement resulting from a given carbon price, or to determine the emissions price that would be needed to achieve a particular level of emissions: for example, if we want to attain abatement equal to a^0, we must set the emissions price to p^0 (Baker, Barron 2013).

2.3.2.1 Effect of Technological change on the MAC curve

Technological change affects the level and the shape of the MAC curve, which in turn influences the optimal level of abatement and the cost savings realized from technological change. Several methods are commonly used to represent the impact of technological change on the MAC curve. Some models explicitly assume that technical change will pivot the MAC curve down, i.e., reduce the MAC multiplicatively. Others represent technical change as impacting the TAC curve, often through pivoting or shifting it down. A third way to represent technical change is through a reduction in the emissions-to-output ratio or the emissions-to-energy ratio (which can sometimes be interpreted as increasing energy efficiency). Another approach is to model technical change as reducing the cost of low-emissions energy. Finally, some models place "knowledge" into the production function, and allow knowledge to substitute for fossil, non-fossil, or overall energy (Baker, Clarke & Shittu 2008). In this thesis we represent technological change through pivots and shifts to the original MAC curve (Figure 3).

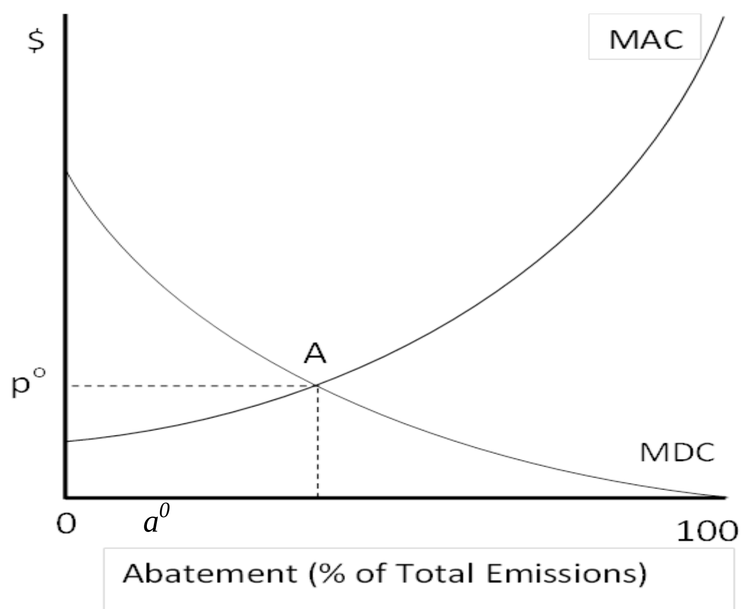

Figure 2: A simple example of the abatement problem.

Modelers should also be aware of the possibility that technological change will have more complex effects than simply reducing the MAC, and that these effects can create perverse incentives. Indeed, under certain conditions technological change can increase the MAC for some levels of abatement, or worse yet, lead to *higher* emissions. Baker, Clarke & Shittu (2008) discuss this matter in some detail and provide a number of examples of this important phenomenon. In a separate paper Baker and Shittu (2006) show that if the elasticity of substitution between fossil fuels and low carbon energy is low enough, the MAC will be *everywhere* increased by technological change.

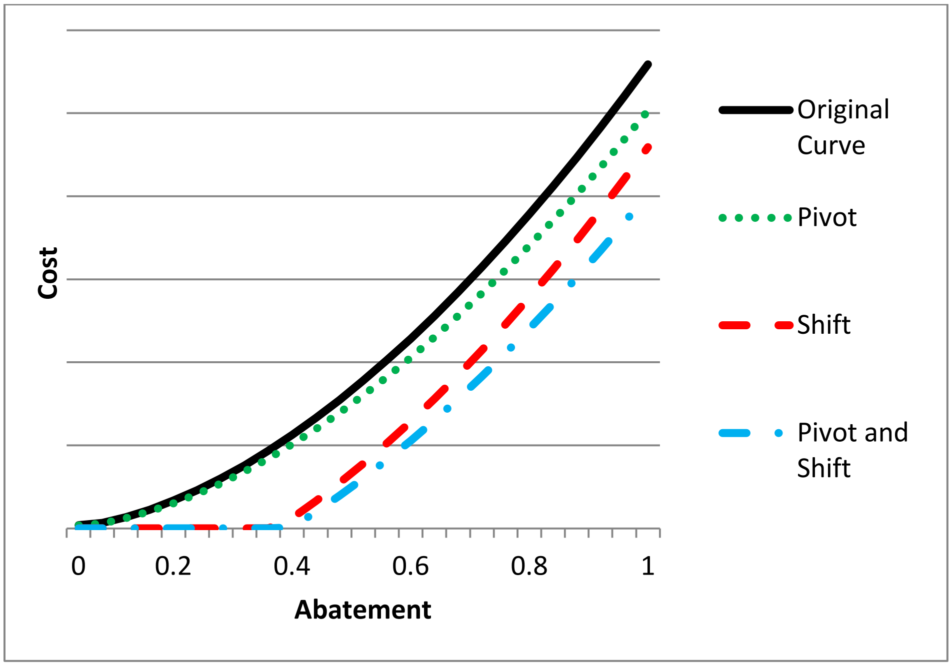

Figure 3: The effect of pivots and shifts on a MAC curve.

To illustrate how technological change can increase the MAC, Baker, et al. (2008) give the following example: consider a technology that would be used only at low levels of abatement; for example, increasing the efficiency of coal-fired power plants. The resulting TAC and MAC curves are illustrated in Figure 4. Such a technology would significantly reduce the TAC at low levels of abatement (left panel of Figure 4), but it would have little effect at higher levels because society would be burning little coal. Therefore, while the TAC is always lower (and the firm strictly better off), the MAC is higher at high levels of abatement (right panel of Figure 4).

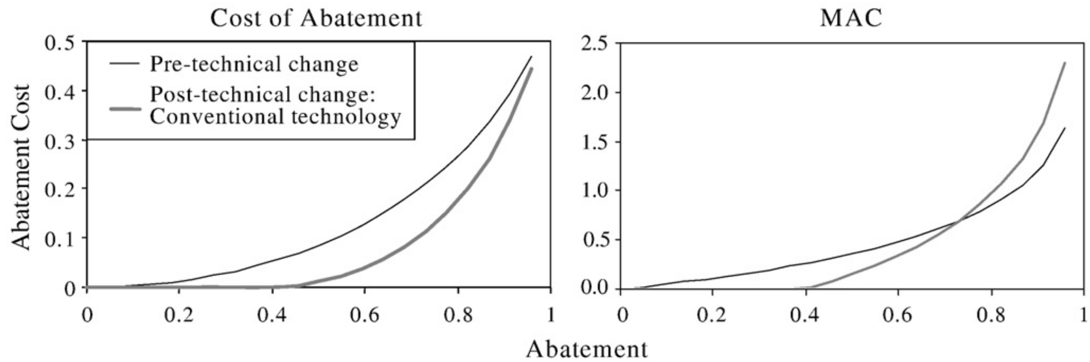

Figure 4: TAC curves before technological change and the resulting MAC curves (Reproduced from Baker, Clarke, & Shittu (2008)).

One risk posed by technological change that increases the MAC are perverse incentives. Under certain conditions, optimal emissions increase (for a given tax) after technological change. This may occur if a breakthrough in a low-efficiency abatement technology reduces the cost of low abatement to the point that a firm is better off employing the low-cost, low-efficiency abatement technology and paying the higher tax, rather than employing a high-cost, high-efficiency abatement technology and paying a lower tax (Baker et al. 2008) .

2.4 Integrated Assessment Models

IAMs can be broadly grouped into two categories: bottom-up models simulate the economy through detailed technological models, and top-down models optimize theoretically consistent, highly aggregated representations of the economy (Kahouli-Brahmi 2008). Bottom-up models are generally used to determine the most cost effective way to deal with a given policy from a microeconomic standpoint, while top down models are used to analyze the macroeconomic effects of policy (Rivers, Jaccard 2005, Popp 2004). In other words, top down models are useful for deciding where to go, and bottom up models are used to decide how to get there.

2.4.1 Endogenous Technological Change in IAMs

One approach to modeling technological change endogenously in IAMs is the learning curve approach—technology is assumed to improve as a function of experience. Although common, this method is not without problems; the learning parameter is technology-specific, so there is no way to aggregate individual learning parameters because the aggregate parameter would change as the composition of the market varied. The implication here is that there is no single learning parameter that can be applied to the entire market. Nordhaus (2008) notes this and several other potential problems with using a learning model to endodgenize technological change, including a statistical identification problem in trying to separate learning from other technological change (such as scale effects), and a propensity to bias optimization models toward technologies with (incorrectly) high learning coefficients. Examples of these difficulties can be found elsewhere in the literature: Nemet (2006) examined the factors affecting the price of solar photovoltaics and concluded that learning by doing has a poor correlation with price for solar photovoltaics, and Yu, van Sark and Alsema (2011) noted a similar problem, attributing the issue to the effect of scale and scarcity effects. Soderholm and Sundqvist (2007) note that scale effects can cause upward bias in the learning parameter for increasing returns to scale.

There can be little doubt that using the learning model has obstacles, but there are ways to address the issues. Yu et al. (2011) and Soderholm and Sundqvist (2007) advocate the use of multi factor learning curves. This approach decomposes the drivers of technological change into potentially any number of components: scale, learning, and scarcity could, in theory, all be separately modeled. Soderholm and Sundqvist (2007) also discuss the importance of choosing the appropriate proxy for learning: installed capacity, demand, and total generation have all been proposed, and all lead to different results.

2.4.2 The DICE Model

The DICE model was developed by Yale economist William Nordhaus in the early 1990s *"to improve our understanding of the interaction of economy and climate and to design better approaches to economic policy"* (Nordhaus 1994). Here we briefly discuss the DICE model, in particular its treatment of technological change and the abatement cost function.

DICE's objective function is:

$$\max W = \sum_{t=1}^{tmax} U[c(t), L(t)]R(t) \tag{1}$$

where W is welfare, U is utility, L is population, c is per-capita consumption, and R is the discount multiplier. L and R are exogenous, and $c(t)$ is given by:

$$c(t) = \frac{C(t)}{L(t)} = \frac{Q(\Omega, \Lambda, t) - I(t)}{L(t)} \tag{2}$$

where Q is the net output of society after damages Ω and abatement Λ, and I is investment. The full equation for Q is:

$$Q(\Omega, \Lambda, t) = \Omega(T, t)\big(1 - \Lambda(\mu, t)\big)A(t)K(I, t)^{\gamma}L(t)^{1-\gamma} \tag{3}$$

Note that this is the familiar Cobb-Douglass utility function with additional terms for damages and abatement.

The cost of abatement is given by

$$\Lambda(t) = \pi(t)\theta_1(\mathrm{t})\mu(t)^{\theta_2} \tag{4}$$

where the participation cost markup $\pi(t)$ reflects the increasing cost of abatement in the face of incomplete participation due to the fact that participants must abate at a higher and more expensive level than they otherwise would in order to make up for the non-participants, and $\theta_{1,}\theta_2$ are calibration parameters that represent the adjusted cost for the backstop technology (the price of replacing all fossil fuels with other technologies), and the increasing marginal cost of abatement as abatement level rises, respectively.

In DICE, there are two distinct forms of technological change: total factor productivity $A(t)$, from the familiar Cobb-Douglass utility function, and carbon saving technological change σ, which is modeled as a reduction in the carbon intensity of economic activity. Total factor productivity is a parameter that represents the increased output resulting from improved technology. Sigma plays a similar role in the abatement cost equation: as sigma decreases so does the cost of abatement.

2.4.3 The Global Change Assessment Model (GCAM)

The Global Change Assessment Model (GCAM) is a bottom-up IAM developed and maintained by the (Joint Global Change Research Institute 2012b). GCAM differs from DICE in that it is a technologically detailed model that simulates the economy, with a particular emphasis on energy systems. GCAM's detail makes it well suited to questions concerning specific technologies. GCAM plays three important roles in our thesis: we use it to estimate the energy intensity of the economy (section 3.6.1), to calculate the initial value of the cost of backup electricity (section 3.4.2), and to parameterize the effect of solar price on the cost of abatement (section 3.6.4).

CHAPTER 3

THE DICE-S MODEL

3.1 Overview

In this thesis we restrict our scope to CO2 emissions; therefore, we use the term "clean" to refer to any energy technology that does not emit CO2, without regard to any other pollutants it may generate (e.g. nuclear waste). Our strategy is to modify DICE to model the clean energy market endogenously and adjust abatement cost accordingly. We implement this in four parts: sizing the market, competitively apportioning that market, adjusting technology prices, and adjusting the cost of abatement (Figure 5).

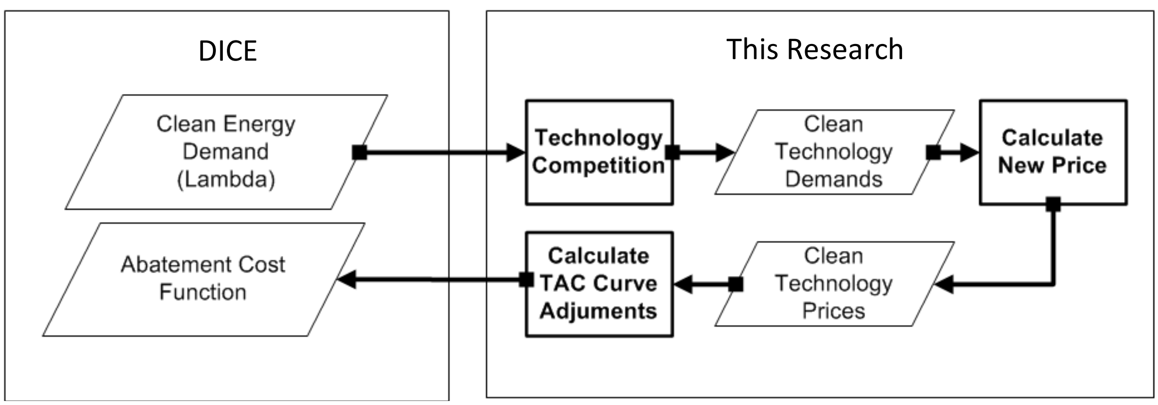

Figure 5: Schematic of the DICE-S model.

3.2 Sizing the Market

We begin by determining the energy demanded by the economy. We will distinguish between two demands: the total demand for energy in the economy, and the demand for clean energy; we term the former "absolute demand", and refer to the latter as "clean demand", or simply "demand". The absolute demand for energy in the economy is given by

$$D_{Abs}(t) = \tau(t) * Y_{gross}(t) \tag{5}$$

where Y_{gross} is global GDP in trillions of dollars and the parameter τ is the energy intensity of the economy in GWh/Trillion \$. D_{clean}, the per-period demand for clean energy in GWh, is calculated by multiplying absolute demand by the abatement level $\mu(t)$. Abatement and GDP are native to DICE; the parameter tau is estimated using GCAM.

3.3 Apportioning the Market

Once the size of the market has been determined, that market must be apportioned across the available technologies. Cost minimization implies that a single agent model such as DICE would choose the least expensive technology to the exclusion of all others, and that any LBD effects would only increase the price gap. In reality the market is composed of many agents, each solving their own unique optimization problem. Variations in the agents' problems mean that many technologies can survive, resulting in a market with multiple viable technologies apportioned roughly according to price. Our challenge here is to represent such a market in DICE. The logit choice framework (McFadden 1974) offers a compact, well-behaved means of allocating market share in a way that meets this requirement.

The general form of the logit share equation is:

$$s_i = \frac{b_i p_i{}^{-\gamma_i}}{b_i p_i{}^{-\gamma_i} + \sum_{j \neq i} b_j p_j{}^{-\gamma_j}} \tag{6}$$

where s is market share, p is price, b is the base share weight parameter, γ is the price exponent, i is the technology of interest, and j indexes the balance of the market (BOM).

We implement a simplified model of the clean energy market, with the BOM aggregated into a single good. It is straightforward to show that in the two good case b_j is redundant; the functional form used in our model is shown in Equation (7):

$$s_{Sol} = \frac{b_{Sol} p_{Sol}{}^{-\gamma_{Sol}}}{b_{Sol} p_{Sol}{}^{-\gamma_{Sol}} + p_{BOM}{}^{-\gamma_{BOM}}} \tag{7}$$

where s_{Sol} is solar's share of the clean energy market.

The market share of solar is used to calculate the demand for solar D_{Sol} by multiplying absolute demand D_{Abs} by abatement μ and solar share s_{Sol} to obtain the demand for solar energy in GWh:

$$D_{Sol} = D_{Abs} * \mu * s_{Sol} \tag{8}$$

3.4 Solar Price

In the previous sections we discussed how the model arrives at the demand for solar energy. Here we discuss how solar demand affects its price. The price of solar technology has two components: the cost of the solar technology itself, and grid integration costs incurred due to the intermittent nature of solar energy. The net price of solar energy is given by:

$$p_{Sol}(\mathrm{T}) = C_{Tech}(T) + C_{Int}(T) \tag{9}$$

Where $C_{Tech}(T)$ and $C_{Int}(T)$ represent the cost of base solar technology and the integration cost, respectively.

3.4.1 Technology Cost

We implement technological learning in solar photovoltaics as a return to scale. We assume that the price of solar responds to scale after Nemet (2006) and adopt the functional form of Nemet and Baker (2009) as shown in (10)**,** using demand as a proxy for installed capacity:

$$C_{Tech}(\mathrm{T}+1) = C_{Tech}(T)\left(\frac{D_{\mathrm{Sol}}(T+1)}{D_{\mathrm{Sol}}(T)}\right)^{-\varphi_{Sol}} \tag{10}$$

where C_{Tech} represents the cost of the base solar technology in \$/GWh, and φ_{Sol} is the Return To Scale (RTS) parameter.

3.4.2 Integration Cost

The intermittent nature of solar energy imposes integration costs on the electricity distribution grid (grid). At low levels of market share these costs are negligible, but the costs increase significantly as market share increases. We follow the standard assumption in GCAM, that the integration issues are solved by building gas turbine backup capacity, with a 1:1 backup ratio needed when the market share of solar reaches approximately 20%.

The cost of backup electricity is given by:

$$C_{Int} = C_{Back} * \rho \tag{11}$$

where C_{Int} is the cost of integration in \$/GWh, C_{Back} is the cost of the backup technology (the gas turbines) in \$/GWh, and ρ is the backup ratio.

The backup ratio is given by a logistic function:

$$C_{Int} = C_{Back} * \left(1 - \frac{1}{e^{a*max[(S_{Sol} - S_{Sol}^{*}),0]}}\right) \tag{12}$$

where S_{Sol} is the market share of solar; S_{Sol}^{*} is the integration cost threshold, the market share requiring a 50% backup ratio; and a is a parameter controlling how steeply the backup requirement increases.

The parameter C_{Back} is derived from GCAM and represents the cost of gas turbine generation at a 5% utilization factor (Joint Global Change Research Institute 2012a). The initial value for C_{Back} is the 2005 cost of backup electricity under the GCAM default scenario. This cost improves over time at the same rate as $\theta_1(t)$, the adjusted cost of the backstop technology in DICE. The equation for C_{Back} is :

$$C_{Back}(t) = C_{Back}(1) * \left(\frac{\theta_1(t)}{\theta_1(1)}\right) \tag{13}$$

3.5 Changing the TAC curve

In the previous sections of this chapter we've discussed the model of the clean energy market itself: the level of abatement determines clean demand, solar's market share (and demand) is determined according to its price, and the next period's solar price is determined by growth in demand for solar. Now we turn our discussion to how changes in the clean energy market affect the cost of abatement in the economy as a whole.

Recall from section 2.3.1 that abatement is a complex phenomenon involving many factors in addition to technology cost. The complexity of the abatement phenomenon prevents us from turning directly to theory to construct our model. Instead, we follow the lead of Baker and Solak (2011) , and use a bottom up model to simulate the economy under a series of assumptions about the price of technology, generate abatement cost curves from those simulations, and parameterize these changes as pivots and shifts to the MAC curve. The modified MAC curve is:

$$\widetilde{MAC}(\mu;\ \alpha,\ h) = (1 - \alpha(p_{Sol}))[MAC(\mu) - h(p_{Sol}) * MAC(0.5)] \tag{14}$$

where α and h are the pivot and shift terms (see section 2.3.2.1), respectively, and MAC (0.5) is an arbitrary "anchor point" on the baseline MAC curve. Since DICE does not explicitly contain a MAC curve, in order to apply this method to the DICE model, we integrate the MAC curve with respect to abatement:

$$\widetilde{TAC}(\mu;\ \alpha,\ h) = (1 - \alpha(p_{Sol}))[TAC(\mu) - h(p_{Sol}) * MAC(0.5)\mu] \tag{15}$$

and substitute the result into the original TAC equation in the DICE model.

The revised TAC in (15) closes the loop shown in Figure 5. The level of abatement determines the demand for clean energy, the price of solar determines the share of that demand captured by solar (and therefore solar demand), which in turn affects the future price of solar. As the price of solar changes, the TAC also changes, which shifts the optimal level of abatement.

3.6 Model Calibration

Before the model can be used, it must be calibrated. In order to calibrate the model we estimate the relevant economic variables and select appropriate parameter values for the logit choice equation.

3.6.1 Energy Intensity of the Economy (τ)

In order to calculate the demand for clean energy in GWh we must estimate the energy intensity of the economy τ in kWh/$. For this estimation we use the Global Change Assessment Model (GCAM). We calculate τ for the default settings of GCAM and extrapolate this curve into the future (Figure 6). Table 1 summarizes the data used in the calculation. Our price deflators are taken from the Bureau of Economic Analysis National Income and Product Accounts (NIPA) Table 1.1.9, Implicit Price Deflators for Gross Domestic Product (Bureau of Economic Analysis 2013).

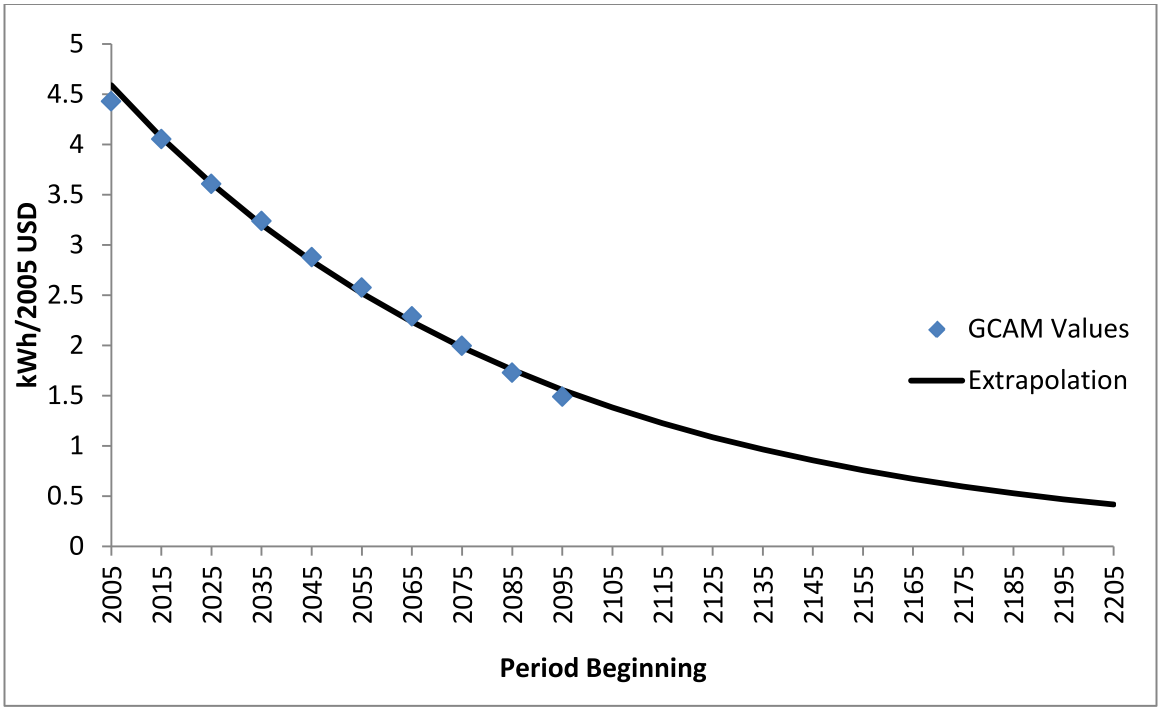

Figure 6: Estimation of tau.

Table 1: Energy intensity of the economy in GCAM (continued on next page).

Year	Primary Energy Consumption (EJ)	GDP (MM 1990 USD)	kWh/1990 USD	kWh/2005 USD
1975	160.46	1.21E+07	3.69	2.66
1990	496.35	1.95E+07	7.07	5.11
2005	660.91	3.00E+07	6.13	4.43
2010	699.75	3.26E+07	5.95	4.30
2015	756.59	3.75E+07	5.61	4.05
2020	818.58	4.28E+07	5.31	3.83
2025	878.19	4.89E+07	4.99	3.61
2030	943.95	5.55E+07	4.73	3.42
2035	1011.80	6.27E+07	4.48	3.24
2040	1076.56	7.10E+07	4.21	3.05
2045	1145.73	7.99E+07	3.98	2.88
2050	1226.45	9.02E+07	3.78	2.73
2055	1296.65	1.01E+08	3.56	2.58
2060	1370.88	1.13E+08	3.36	2.42
2065	1448.44	1.27E+08	3.17	2.29
2070	1518.62	1.42E+08	2.96	2.14
2075	1586.92	1.59E+08	2.76	2.00

2080	1651.95	1.78E+08	2.57	1.86
2085	1707.15	1.98E+08	2.39	1.73
2090	1758.26	2.20E+08	2.22	1.60
2095	1804.53	2.43E+08	2.06	1.49

3.6.2 Backup Price

Backup price is calculated using GCAM default assumptions. The initial backup price is the price of backup electricity in 2005 under GCAM default assumptions. Table 2 summarizes the data used to calculate the initial cost of backup electricity (Table 3). The base cost of backup electricity improves at the same rate as the backstop price (see section 3.4.2). Figure 7 illustrates the cost pathway for backup electricity: the initial cost is approximately $63/Mwh, and declines by approximately 50% per century.

Table 2: Backup electricity in GCAM (continued on next page).

Region	Sector	Variable	Units	2005
USA	backup_electricity	production	EJ	1.30E-07
USA	backup_electricity	price	1975$/GJ	5.84895
Canada	backup_electricity	production	EJ	1.68E-08
Canada	backup_electricity	price	1975$/GJ	5.94683
Western Europe	backup_electricity	production	EJ	4.14E-07
Western Europe	backup_electricity	price	1975$/GJ	5.85464
Japan	backup_electricity	production	EJ	2.76E-08
Japan	backup_electricity	price	1975$/GJ	6.20995
Australia_NZ	backup_electricity	production	EJ	9.51E-09
Australia_NZ	backup_electricity	price	1975$/GJ	5.9715
Former Soviet Union	backup_electricity	production	EJ	3.04E-08
Former Soviet Union	backup_electricity	price	1975$/GJ	6.07292
China	backup_electricity	production	EJ	0
China	backup_electricity	price	1975$/GJ	8.2326
Middle East	backup_electricity	production	EJ	1.43E-08
Middle East	backup_electricity	price	1975$/GJ	5.70526
Africa	backup_electricity	production	EJ	1.55E-08
Africa	backup_electricity	price	1975$/GJ	5.78204

Latin America	backup_electricity	production	EJ	2.62E-08
Latin America	backup_electricity	price	1975$/GJ	5.76034
Southeast Asia	backup_electricity	production	EJ	1.91E-08
Southeast Asia	backup_electricity	price	1975$/GJ	5.91783
Eastern Europe	backup_electricity	production	EJ	1.09E-08
Eastern Europe	backup_electricity	price	1975$/GJ	5.97388
Korea	backup_electricity	production	EJ	8.42E-09
Korea	backup_electricity	price	1975$/GJ	6.03642
India	backup_electricity	production	EJ	3.03E-08
India	backup_electricity	price	1975$/GJ	5.6331

Table 3: Initial price of backup electricity.

GCAM Units	1975$/GJ	5.87
DICE Units	2005$/GWh	62.93

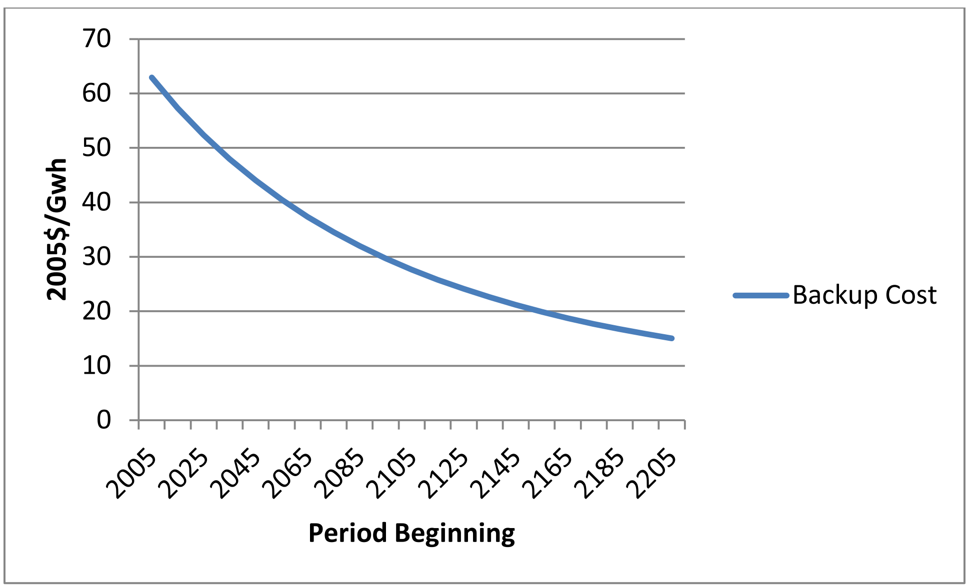

Figure 7: Price pathway of backup electricity.

3.6.3 The Logit Choice Equation

The logit choice function is calibrated based on the initial technology prices and the assumption that when prices are equal technologies will have equal market share. We also make the assumption that the base shareweight factor b_i is equal to one, which allows solar to capture up to 100% of the market. These assumptions imply that γ_{Sol} and γ_{BOM} are equal and allow us to solve for their values using our initial technology prices (see section 3.6.5). The final equation is shown in Equation (16).

$$s_i = \frac{p_{Sol}{}^{-4.935}}{p_{Sol}{}^{-4.935} + p_{BOM}{}^{-4.935}} \tag{16}$$

3.6.4 The Pivot and Shift Parameters.

The pivot and shift parameters were calculated after Baker, Chon and Keisler (2009)[2]. We use GCAM to generate MAC curves for a set of different prices of solar PV to obtain a set of estimated pivot and shift terms, one for each set of assumptions (Table 4). Next, we normalized the initial price of solar (the GCAM default value) to one and fitted an exponential curve to the resulting points using a least-squares regression (Figure 8). By normalizing the price of solar to one we eliminate the need to use deflators to convert between GCAM and DICE units, and can instead consider only the change in price relative to its starting point.

Table 4: Pivot and shift estimates from GCAM.

Solar Cost Assumption ($/kWh)	Normalized Cost (GCAM Default = 1)	Estimated Pivot	Estimated Shift
0.005	0.044	0.08107	0.05294
0.03	0.266	0.03704	0.01983
0.05	0.444	0.01372	0.00824
0.075	0.665	0.01058	0.00587

[2] The author wishes to acknowledge Rose Zdybel for her help in understanding this process and generating the estimates.

The resulting expressions are then used in DICE-S to estimate the pivot and shift as the net price of solar changes. The final equations for the pivot and shift are given in Equation (17) and (18) below.

$$\alpha(p_{Sol}) = .0875e^{-3.454p_{Sol}} \tag{17}$$

$$h(p_{Sol}) = .0548e^{-3.646p_{Sol}} \tag{18}$$

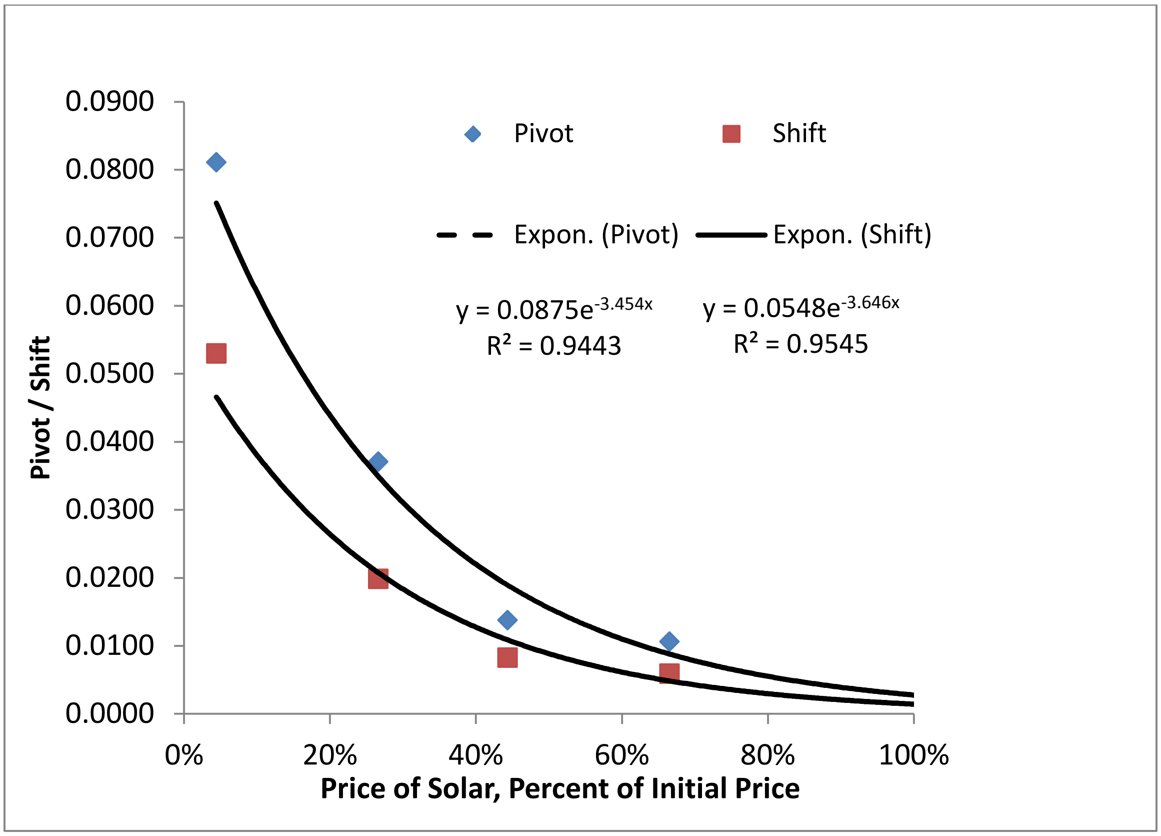

Figure 8: Pivot and shift parameters.

3.6.5 Technology Price Estimates

In DICE-S, the price of clean energy technologies is given in the form of the Levelized Cost of Electricity (LCOE), the final "bottom line" price of generated electricity. LCOE data is highly variable because of the many factors which affect the final value. In addition to the technology cost, the cost of capital, system lifetime, and discount rate all impact the LCOE. This variability is reflected in the wide range of values reflected in the literature (Table 5).

Table 5: Levelized Electricity costs in $/GWh used for price path (Lazard 2010, Energy Information Administration , Jones 2012, IRENA 2012).

	Lazard		EIA TCDB		NREL Energy Analysis Office (2005)		IEA		IRENA	
	Low	High	Low	High	Low	High	Low	High	Low	High
Nuclear	70	104	41	56						
Biomass	74	124	40	92			60	250		
Geothermal	68	126	37	37	30	50	40	200		
Solar Thermal	108	177	199	302	100	170	155	300		
Hydro			19	19			20	230	12	190
Wind	59	158	40	123	40	60	40	300		
Solar PV	122	175	281	433	200	300	110	400		

For each technology's price estimate we choose the median value of the range of price estimates for each individual technology. We calculate the price for the BOM as a weighted average of the median value of each component technology’s price estimates with respect to market share based on generation information from the International Energy Agency (IEA 2009). In order to make the generation data consistent with the cost data we aggregate all biomass technologies and municipal waste into a single category and aggregate tide, wave and ocean into hydropower. The resulting figures for the BOM are given in Table 7.

Table 6: Electric generation (GWh) in 2009 (IEA 2009).

Municipal Waste*	**58152**
Industrial Waste	**12698**
Primary Solid Biofuels**	**174596**
Biogases	**37856**
Liquid Biofuels	**4811**
Geothermal	**66672**
Solar Thermal	**842**
Hydro	**3328627**
Solar Photovoltaics	**20155**
Tide, Wave, Ocean	**530**
Wind	**273153**
Nuclear	**2696765**

Table 7: Technology cost values ($/GWh).

	Cost	**Share**
BOM	77.90	0.9970
Solar PV	252.64	0.0030

3.6.6 Scale Parameters

The RTS factor φ of the solar market is the final element of the calibration process. We select a range of scale factors from .15 to .25 based on the literature (Nemet, Baker 2009, Breyer, Gerlach 2013).

3.7 Solver Configuration

The final step in the calibration process is to adapt the model to its solver. In this thesis we use the CONOPT3 solver (Drud 2008). Initial testing of the model revealed three significant issues: poor quality initial points, excessively long solution times, and stalling. In order to address these issues we specified an alternate starting point, rewrote the model to improve solvability, and employed an iterative solving technique.

By default, CONOPT3 initializes all variables to zero (Drud 2008). This resulted in a poor quality initial point due to a large number of zero derivatives as well as undefined denominators in several equations. Additionally, during solution runs some variables became small enough to produce extremely large derivatives. These issues were addressed by assigning lower limits to certain critical variables (Table 8) and using the base abatement pathway as an initial point for the optimization.

In some cases, solution times were excessively long due to CONOPT's difficulty handling expressions in nonlinear functions, products, and quotients (Drud 2008). Editing DICE to minimize the occurrence of these functions significantly improved the model's performance, reducing the number of iterations from 762 to 244 (67%). We then used our edited version of DICE as the basis for DICE-S.

Stalling issues were addressed by iterative solving. This technique capitalizes on the fact that CONOPT3 calculates an initial point using one method and then switches to another method to refine the solution (Drud 2008). Therefore, in cases where the solver was unable to reach an optimal solution due to stalling the solver was able to "jump" to another nearby point to restart the solution process. The final model code is given in the appendix.

.

Table 8: Summary of stability constraints.

Variable	Constraint	Reason
Miu	Initial value set to baseline run optimal value	Reduce zero derivatives. Start search near baseline optimal.
SolDemandRat	>1	Theoretical consistency (prevents increasing prices).
Omegadenom	>1	Theoretical consistency (enforces CO2 as a bad)
SolNetPrice	<400	Prevents overflows in model.
SolDemand	>0.0000005 to >0.00005	Prevents overflows in model.
SolPriceDenom	>1	Theoretical consistency (prevents increasing prices).

In this chapter we have discussed how the DICE-S model models the clean energy market, how that market affects the cost of abatement, the calibration of the model, and the steps we took to adapt the model to the CONPT solver. DICE-S uses a multi-step process to model the effect of solar price on the cost of abatement. DICE-S uses the level of abatement to determine the size of the clean energy market, the relative prices of solar energy and the BOM determine the market share of solar (and therefore demand) within that market, and the price of solar is adjusted based on the market share and total demand for solar. The cost of abatement is modeled as a function of solar price according to a parameterization generated by a bottom up simulation model (GCAM). We calibrate the model according to a series of assumptions about market behavior drawn from theory and the literature. Finally, we make minor changes to the model to allow it to run on our selected solver.

CHAPTER 4

RESULTS

4.1 Overview

Here we present the results of the model runs. For our analysis we select three levels of the RTS factor: 15, 20, and 25%, based on the range of estimates found in the literature (Nemet, Baker 2009, Breyer, Gerlach 2013). In what follows we shall refer to the 15, 20, and 25% scenarios as the low, medium, and high scenarios, respectively. In all cases full abatement is reached by 2205; therefore, we limit our discussion to the period prior to 2205.

4.2 The Solar Market

The solar market changes significantly as the RTS factor changes: in the low scenario solar remains a small part of the market; in the middle level the solar market share rises to the integration cost threshold and remains there; and in the high scenario the solar captures most of the market (Figure 9). We note the non-monotonic behavior of market share in the low scenario, which is caused by the stepwise behavior of the abatement curve (see Section 4.3). The price of the base technology remains high in the low scenario, falls to approximately the BOM price in the medium scenario, and declines to almost nothing in the high scenario (Figure 10).

Figure 11 illustrates how the integration cost remains negligible in the low scenario, but rises significantly in the other two scenarios before declining through time. It is important to note that the declining integration cost is due to the underlying backup technology becoming cheaper over time, not declining market share. Finally, in Figure 12 we see that the net cost of solar falls to just above the BOM price in the low and medium scenarios and falls below the BOM price in the high scenario.

This behavior suggests that there is a critical value of RTS factor below which the base technology remains costly enough that integration costs restrict market growth, and above which the base technology is so inexpensive that the net cost of solar is essentially all from integration costs.

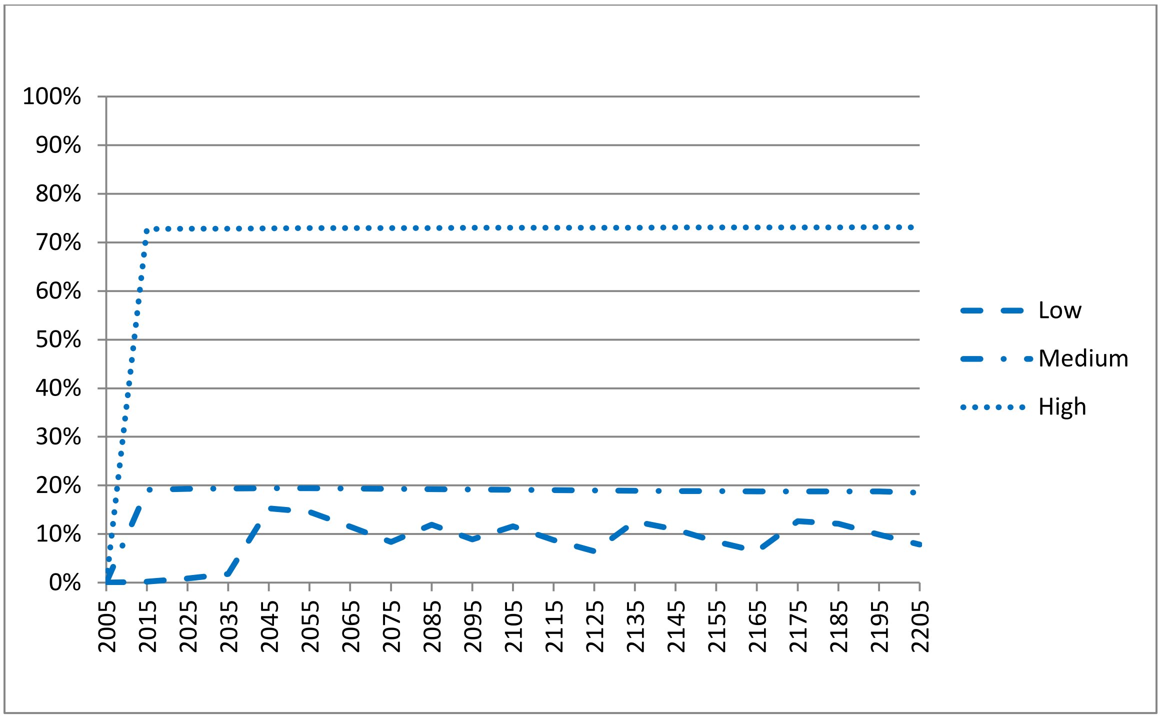

Figure 9: Market share of solar.

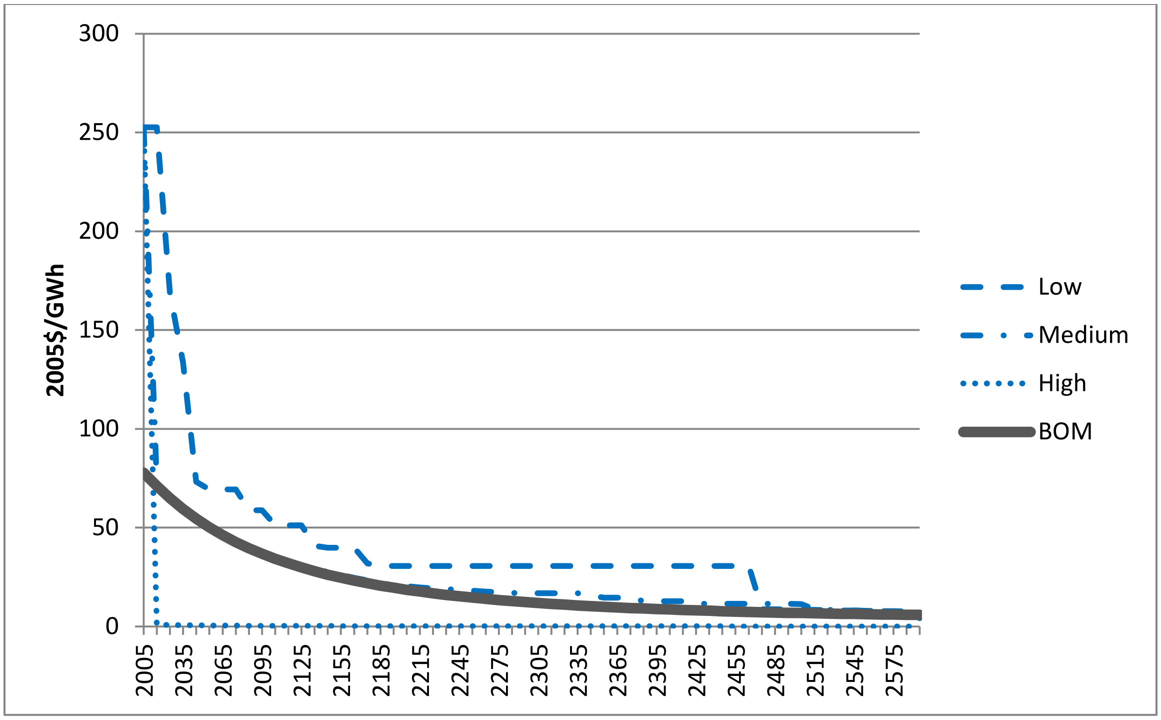

Figure 10: Solar technology price.

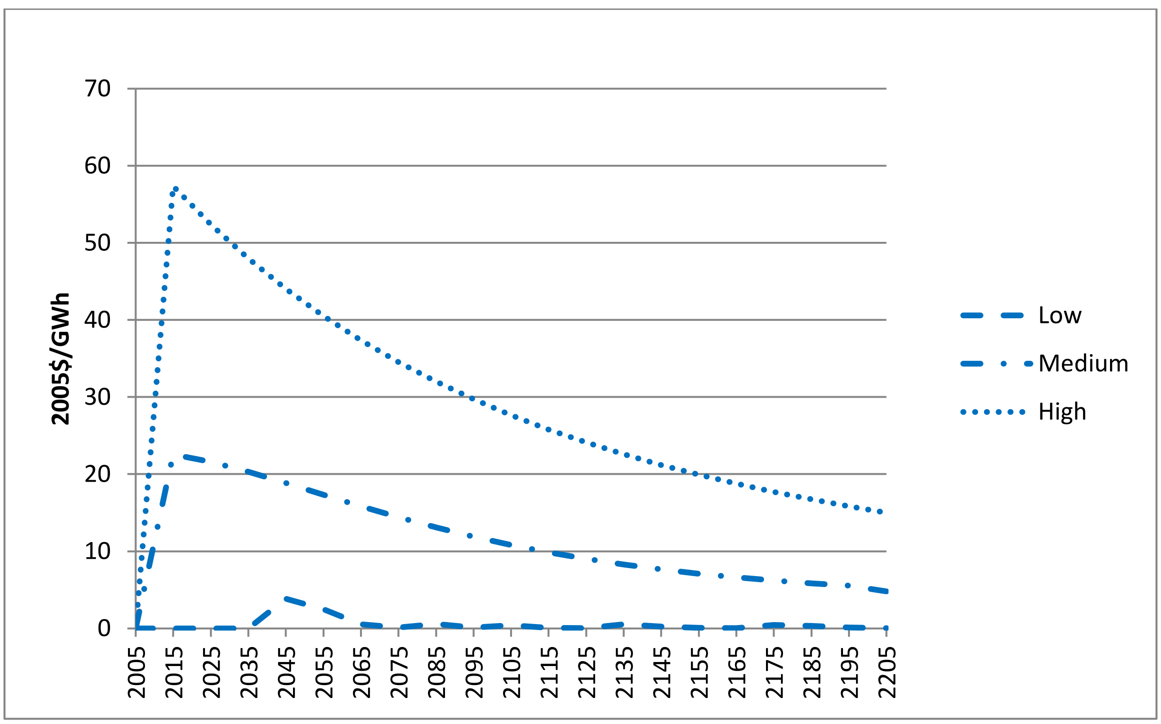

Figure 11: Solar Integration Cost.

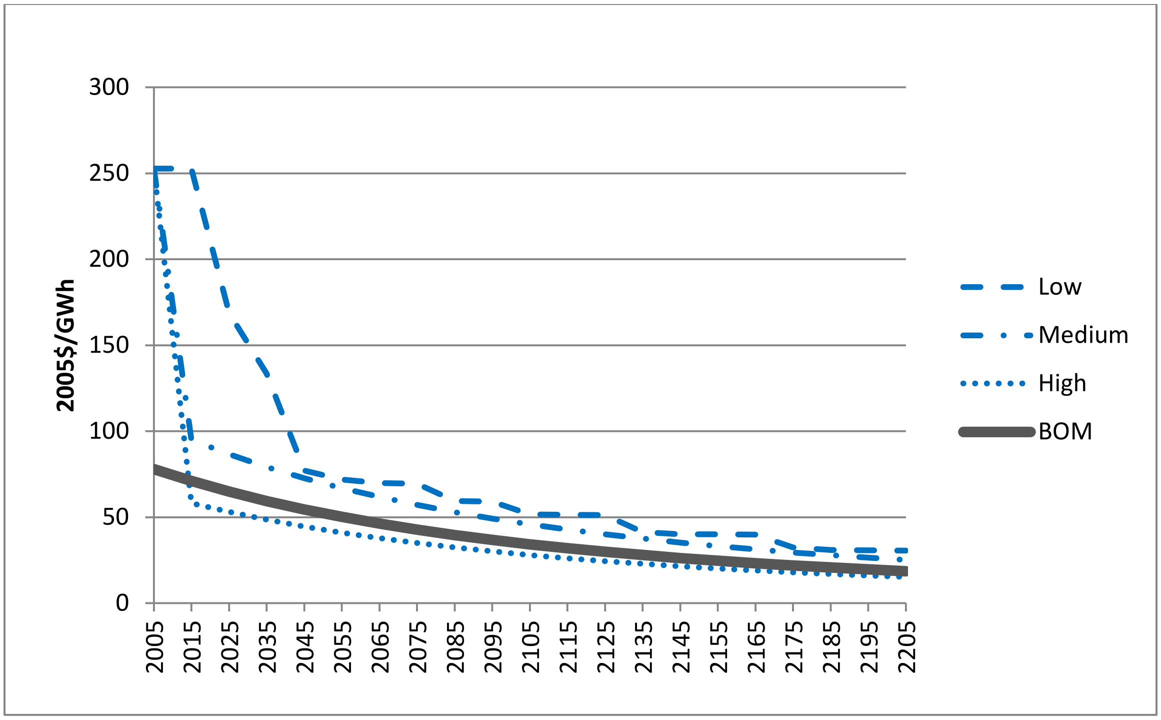

Figure 12: Solar net cost.

Net investment in solar is increasing in RTS factor (Figure 15), but the composition of spending is different. In the low and medium cases the majority of spending is on the technology itself, while in the high scenario spending is almost entirely on integration costs (Figure 13 and Figure 14).

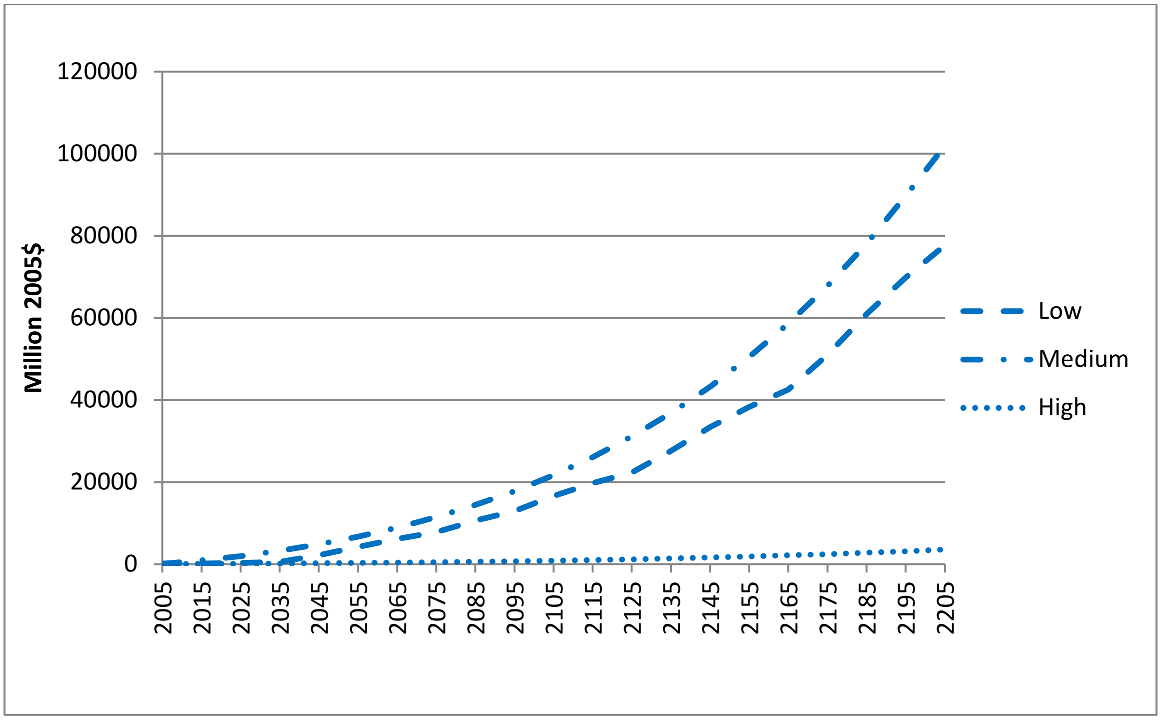

Figure 13: Cumulative Technology Spending.

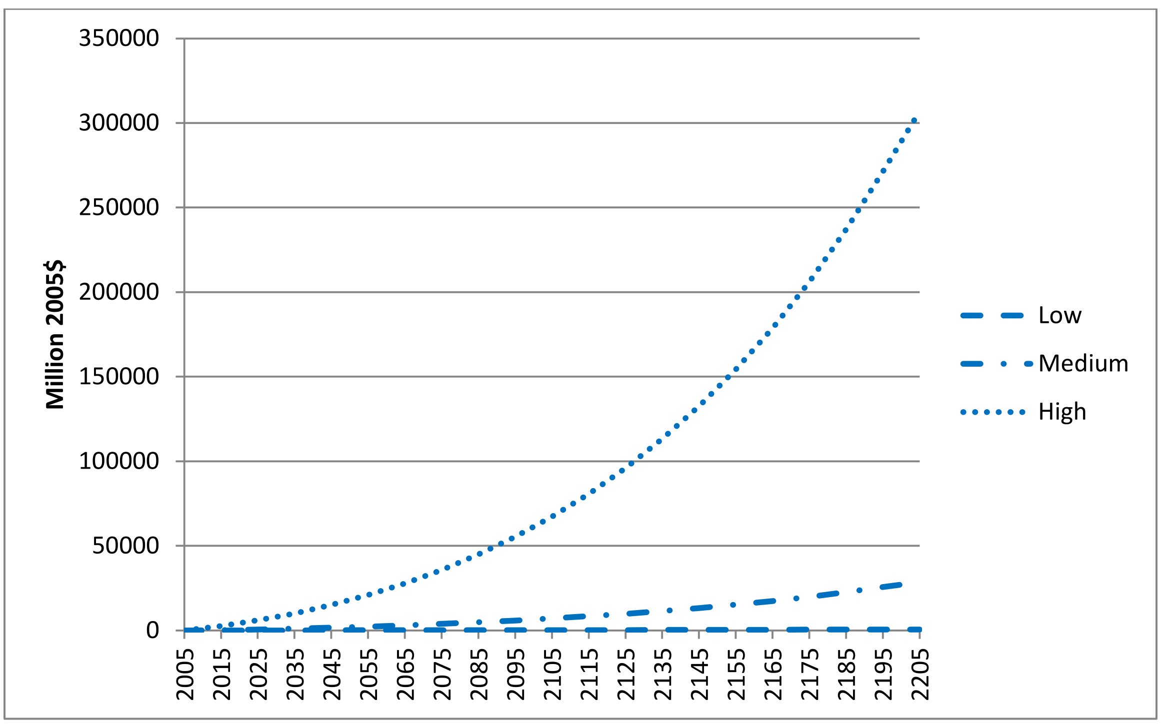

Figure 14: Cumulative Integration Spending.

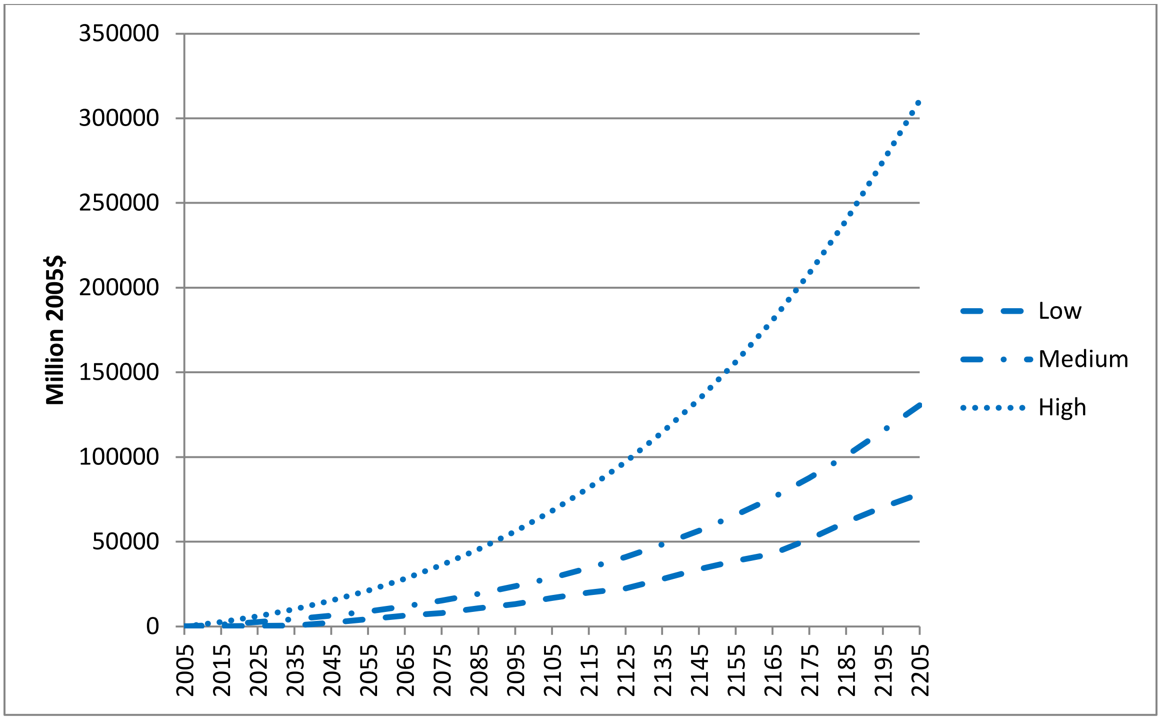

Figure 15: Cumulative Total Spending.

4.3 Abatement

The price of solar affects the cost, and therefore the optimal level, of abatement. Both the pivot and shift increase through time as the solar cost decreases (Figure 16 and Figure 17), resulting in increased abatement versus the baseline case in all cases. In both the high and medium scenarios abatement follows a smooth path similar in shape to the baseline curve (Figure 18); however, in the low scenario the abatement curve increases in a series of steps. This behavior occurs because the model is investing in a large amount of solar to capitalize on the return to scale, then waiting until the market expands, which reduces solar's market share (and therefore integration costs), before investing in additional solar. In the medium and high scenarios the returns to scale are high enough that the model makes its main investment in solar in the first period and subsequent investments in solar simply "track" the declining cost of the BOM.

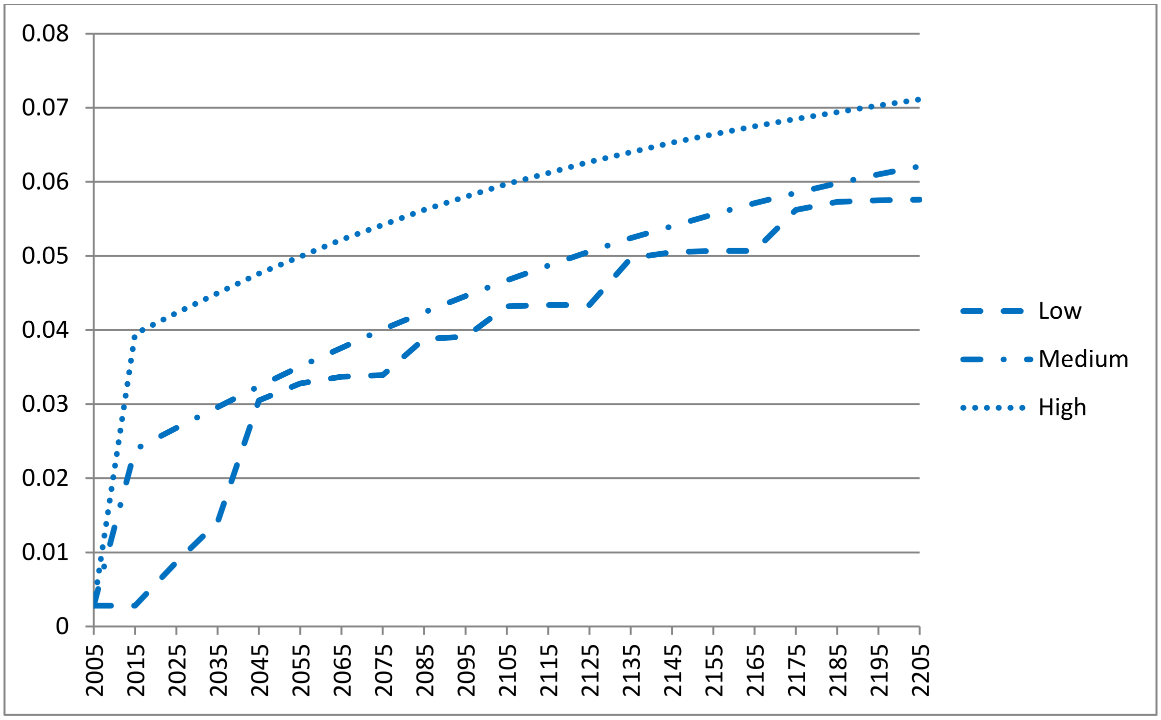

Figure 16: Pivot.

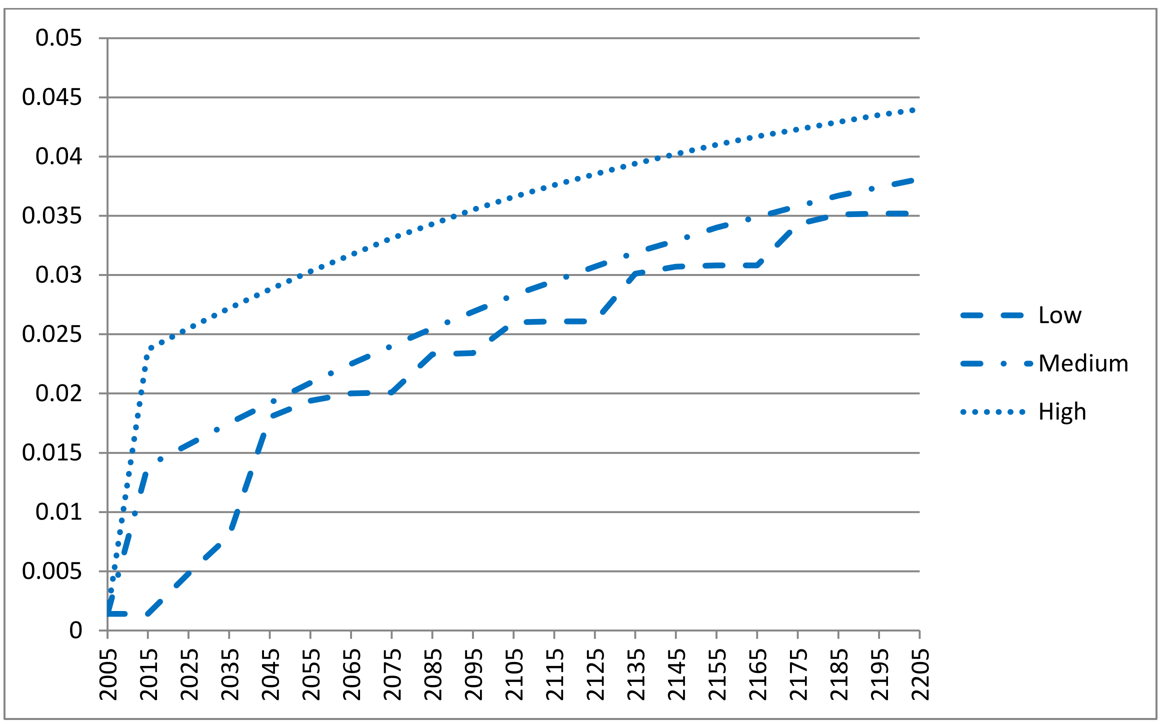

Figure 17: Shift.

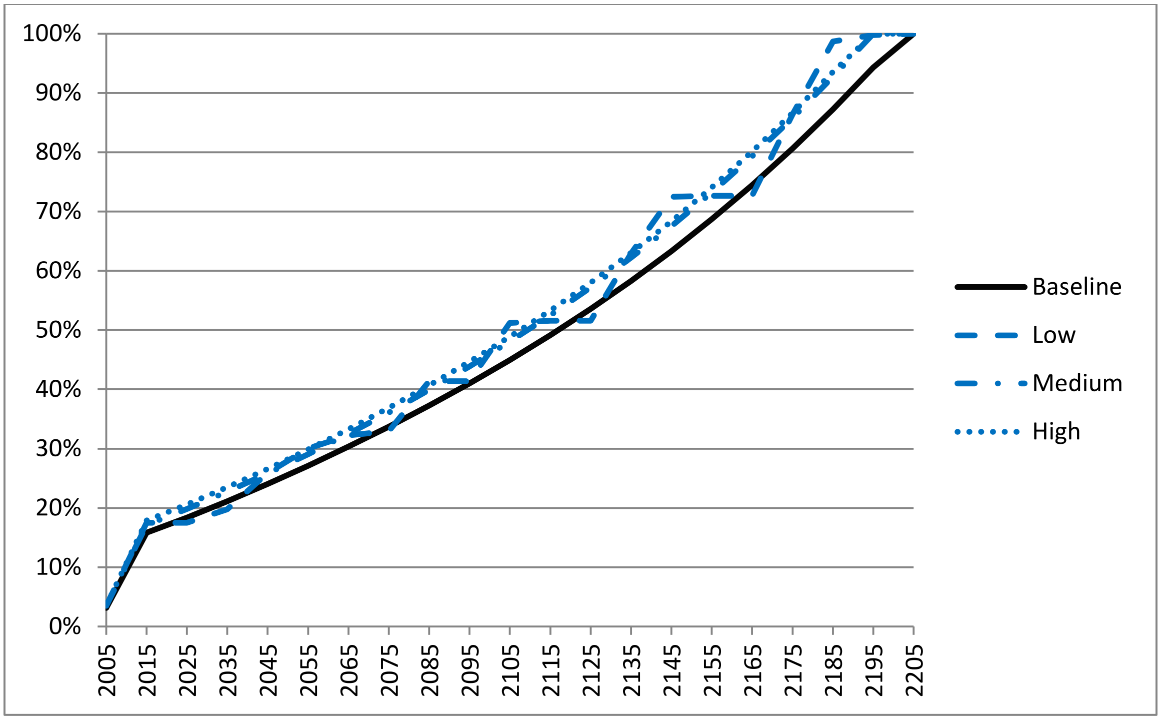

Figure 18: Abatement pathways.

4.4 Environment

Just as with abatement, under the low scenario emissions are not smooth and the medium and high scenarios show a smooth path similar to the baseline case but with improvement (Figure 19). Temperature rise is also improved, with the improvement ranging from 5.8% in the low scenario to 6.1% in the high scenario (Figure 20).

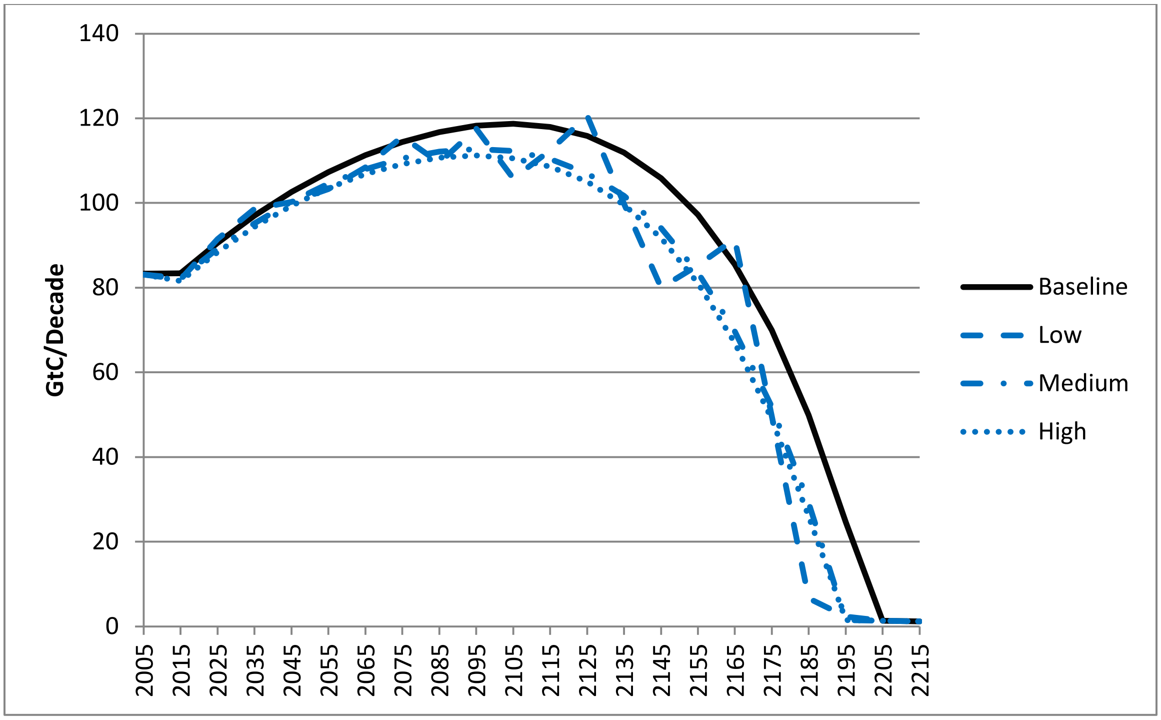

Figure 19: CO2 emission pathways.

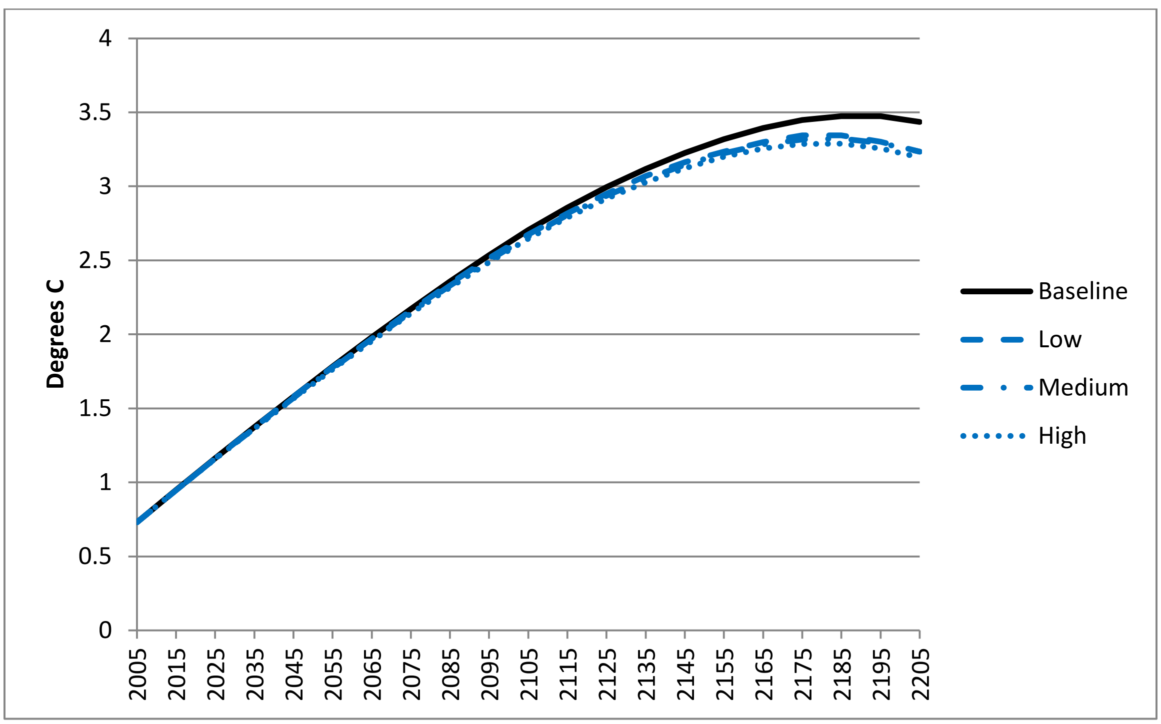

Figure 20: Temperature rise.

4.5 Welfare

Table 9 illustrates the effect of RTS on welfare. The overall welfare improvement ranges from .035 to .068 %, which corresponds to 3.16 to 6.06 percent of the maximum possible benefit if abatement were free.

Table 9: Effect of RTS Factor on Welfare.

	Baseline (Unmodified Model)	Low (15%)	Medium (20%)	High (25%)	Maximum (Free Abatement)
Objective Function Value	150168.3	150221.5	150241.7	150270.5	151856.1
Percent Improvement vs. Baseline	0.000%	0.035%	0.049%	0.068%	1.124%
Percent of Possible Improvement	0.00%	3.16%	4.35%	6.06%	100.00%

4.6 Conclusions

This thesis implemented an endogenous model of solar energy cost in the DICE IAM and the resulting DICE-S model was used to examine the effect of returns to scale on the behavior of solar technology. The behavior of the solar market raises several important questions and points to opportunities for future research. Finally, implementing endogenous technological change highlighted several technical modeling challenges that need to be overcome.

The main insight gained from this thesis is that the behavior of the solar market in DICE-S implies that there are three "zones" of solar behavior: a "low zone" where solar penetrates the market in a series of steps, which leads to non-monotonic emissions through time; a “medium zone” where the cost of the base technology falls low enough to allow the technology into the market, but remains high enough that integration costs arrest solar’s penetration when they become significant; and a “high zone” where the base technology becomes so inexpensive that the cost is essentially all from integration costs. The implication of this behavior is that the optimal allocation of Research and Development (R&D) resources (the optimal R&D portfolio) is dependent on the RTS factor of the solar market: if the RTS factor is low, R&D should focus on the base technology itself, while if its high, R&D should focus on reducing integration costs – R&D on the base technology would be wasted.

4.7 Future Work

These results raise several important questions: how will changing the integration cost threshold affect the clean energy market, how does changing integration cost itself affect the market’s behavior, and what approach to integration costs (moving the threshold or decreasing them) is best?

One shortcoming of DICE-S is that there is no limit on the price improvement of the base technology. While there is evidence that scale is a primary driver of solar technology price, it is likely that other factors play a role as well.

Another concern is modeling how intermittency affects emissions. This thesis models intermittency as increasing the cost of solar, but it neglects the additional emissions caused when the backup capacity is used. As the penetration of solar increases, the emissions due to backup capacity could become significant.

APPENDIX

MODEL CODE

Base Model

```
$ontext

DICE delta version 8

July 17, 2008.

This version is used for the DICE book, A Question of Balance (YUP, 2008).

We have included only the base, Hotelling, and optimal runs.

Exclude statements are removed so that it can run as a self-contained program.

Created September 5, 2008.

Note that this can be loaded into a data reading program,

$offtext

SETS  T              Time periods                    /1*60/ ;

SCALARS

** Preferences

B_ELASMU   Elasticity of marginal utility of consumption     /  2.0    /

B_PRSTP    Initial rate of social time preference per year   / .015    /

** Population and technology

POP0      2005 world population millions                /6514     /

GPOP0     Growth rate of population per decade          /.35      /

POPASYM  Asymptotic population                          / 8600    /

A0        Initial level of total factor productivity   /.02722   /

GA0       Initial growth rate for technology per decade  /.092      /
```

DELA Decline rate of technol change per decade /.001 /

DK Depreciation rate on capital per year /.100 /

GAMA Capital elasticity in production function /.300 /

Q0 2005 world gross output trill 2005 US dollars /61.1 /

K0 2005 value capital trill 2005 US dollars /137. /

** Emissions

SIG0 CO2-equivalent emissions-GNP ratio 2005 /.13418 /

GSIGMA Initial growth of sigma per decade /-.0730 /

DSIG Decline rate of decarbonization per decade /.003 /

DSIG2 Quadratic term in decarbonization / .000 /

ELAND0 Carbon emissions from land 2005(GtC per decade) / 11.000 /

** Carbon cycle

MAT2000 Concentration in atmosphere 2005 (GtC) /808.9 /

MU2000 Concentration in upper strata 2005 (GtC) /1255 /

ML2000 Concentration in lower strata 2005 (GtC) /18365 /

b11 Carbon cycle transition matrix /0.810712 /

b12 Carbon cycle transition matrix /0.189288 /

b21 Carbon cycle transition matrix /0.097213 /

b22 Carbon cycle transition matrix /0.852787 /

b23 Carbon cycle transition matrix /0.05 /

b32 Carbon cycle transition matrix /0.003119 /

b33 Carbon cycle transition matrix /0.996881 /

** Climate model

T2XCO2 Equilibrium temp impact of CO2 doubling oC / 3 /

FEX0 Estimate of 2000 forcings of non-CO2 GHG / -.06 /

FEX1 Estimate of 2100 forcings of non-CO2 GHG / 0.30 /

TOCEAN0 2000 lower strat. temp change (C) from 1900 /.0068 /

TATM0 2000 atmospheric temp change (C)from 1900 /.7307 /

C1 Climate-equation coefficient for upper level /.220 /

C3 Transfer coeffic upper to lower stratum /.300 /

C4 Transfer coeffic for lower level /.050 /

FCO22X Estimated forcings of equilibrium co2 doubling /3.8 /

** Climate damage parameters calibrated for quadratic at 2.5 C for 2105

A1 Damage intercept / 0.00000 /

A2 Damage quadratic term / 0.0028388 /

A3 Damage exponent / 2.00 /

** Abatement cost

THETA2 Exponent of control cost function /2.8 /

PBACK Cost of backstop 2005 000$ per tC 2005 /1.17 /

BACKRAT Ratio initial to final backstop cost / 2 /

GBACK Initial cost decline backstop pc per decade /.05 /

LIMMIU Upper limit on control rate / 1 /

** Participation

PARTFRACT1 Fraction of emissions under control regime 2005 /1 /

PARTFRACT2 Fraction of emissions under control regime 2015 /1 /

PARTFRACT21 Fraction of emissions under control regime 2205 /1 /

DPARTFRACT Decline rate of participation /0 /

** Availability of fossil fuels

FOSSLIM Maximum cumulative extraction fossil fuels / 6000 /

** Scaling and inessential parameters

scale1 Scaling coefficient in the objective function /194 /

scale2 Scaling coefficient in the objective function /381800 /

*Scalars added to original model

ALPHA0 pivot / 0 /

b0 shift / 0 /

FullBack Market share requiring 50% backup / .2 /

TauBase Base point for Tau / 5.1771 /

TauFact Improvement rate for Tau per period / .02 /

SolPrice0 Initial price of solar USD per GWh / 252.64 /

SolPrice2 Second period solar price / 0 /

SolVar Exponent of the solar logit choice equation / 4.935 /

SolRTSFact Solar RTS Factor per doubling / 0 /

BOMPrice0 Inital price for BOM / 77.9 /

BomVar / 4.935 /

* Definitions for outputs of no economic interest

SETS

TFIRST(T)

TLAST(T)

TEARLY(T)

TLATE(T)

TSECOND(T);

PARAMETERS

L(T) Level of population and labor

AL(T) Level of total factor productivity

SIGMA(T) CO2-equivalent-emissions output ratio

R(T) Instantaeous rate of social time preference

RR(T) Average utility social discount rate

GA(T) Growth rate of productivity from 0 to T

FORCOTH(T) Exogenous forcing for other greenhouse gases

GL(T) Growth rate of labor 0 to T

GTHETA1 Growth of cost factor

GSIG(T) Cumulative improvement of energy efficiency

ETREE(T) Emissions from deforestation

THETA1(t) Adjusted cost for backstop

PARTFRACT(T) Fraction of emissions in control regime

AA1 Variable A1

AA2 Variable A2

AA3 Variable A3

ELASMU Variable elasticity of marginal utility of consumption

PRSTP Variable initial rate of social time preference per year

LAM Climate model parameter

```
Gfacpop(T)    Growth factor population

BackPrice(T)  Backup price for Solar

BOMPrice(T)   Balance of Market Price

* The following parameters are added.

TAU(T)        Energy intensity

TauPrime(T)   Decline rate of TAU;

* Unimportant definitions to reset runs

TFIRST(T) = YES$(ORD(T) EQ 1);

TSecond(T) = YES$(ORD(T) EQ 2);

TLAST(T)  = YES$(ORD(T) EQ CARD(T));

TEARLY(T) = YES$(ORD(T) LE 20);

TLATE(T)  = YES$(ORD(T) GE 21);

AA1 = A1;

AA2 = A2;

AA3 = A3;

ELASMU = B_ELASMU;

PRSTP  = B_PRSTP;

b11 = 1 - b12;

b21 = 587.473*B12/1143.894;

b22 = 1 - b21 - b23;

b32 = 1143.894*b23/18340;

b33 = 1 - b32 ;
```

```
* Important parameters for the model

LAM     = FCO22X/ T2XCO2;

Gfacpop(T) =   (exp(gpop0*(ORD(T)-1))-1)/exp(gpop0*(ORD(T)-1));

L(T)=POP0* (1- Gfacpop(T))+Gfacpop(T)*popasym;

ga(T)=ga0*EXP(-dela*10*(ORD(T)-1));

al("1") = a0;

LOOP(T, al(T+1)=al(T)/((1-ga(T))););

gsig(T)=gsigma*EXP(-dsig*10*(ORD(T)-1)-dsig2*10*((ord(t)-1)**2));

sigma("1")=sig0;

LOOP(T,sigma(T+1)=(sigma(T)/((1-gsig(T+1)))););

THETA1(T) = (PBACK*SIGMA(T)/THETA2)* ( (BACKRAT-1+ EXP (-gback*
     (ORD(T)-1)) )/BACKRAT);

ETREE(T) = ELAND0*(1-0.1)**(ord(T)-1);

RR(t)=1/((1+prstp)**(10*(ord(T)-1)));

FORCOTH(T)= FEX0+ .1*(FEX1-FEX0)*(ORD(T)-1)$(ORD(T) LT 12)+
    0.36$(ORD(T) GE 12);

partfract(t) = partfract21;

PARTFRACT(T)$(ord(T)<25) = Partfract21 + (PARTFRACT2-Partfract21)*exp(-
    DPARTFRACT*(ORD(T)-2));

partfract("1")= PARTFRACT1;


* Parameters added
```

TAU(T) = TauBase*exp((ORD(T)-1)*(-TauFact));

BackPrice(T) = 31.684(Theta1(T)/Theta1("1"));

BackPrice(T) = 58.70*(Theta1(T)/Theta1("1"));

BomPrice(T) = BomPrice0*(Theta1(T)/Theta1("1"));

VARIABLES

MIU(T) Emission control rate GHGs

FORC(T) Radiative forcing in watts per m2

TATM(T) Temperature of atmosphere in degrees C

TOCEAN(T) Temperatureof lower oceans degrees C

MAT(T) Carbon concentration in atmosphere GtC

MATAV(T) Average concentrations

MU(T) Carbon concentration in shallow oceans Gtc

ML(T) Carbon concentration in lower oceans GtC

E(T) CO2-equivalent emissions GtC

C(T) Consumption trillions US dollars

K(T) Capital stock trillions US dollars

CPC(T) Per capita consumption thousands US dollars

PCY(t) Per capita income thousands US dollars

I(T) Investment trillions US dollars

S(T) Gross savings rate as fraction of gross world product

RI(T) Real interest rate per annum

Y(T) Gross world product net of abatement and damages

YGROSS(T) Gross world product GROSS of abatement and damages

YNET(T) Output net of damages equation

DAMAGES(T) Damages

ABATECOST(T) Cost of emissions reductions

CCA(T) Cumulative industrial carbon emissions GTC

PERIODU(t) One period utility function

UTILITY

* Added to syncronize notation with Balance

PI(T) Participation cost markup

OMEGA(T) Damage factor

LAMBDA(T) Abatement cost factor

*Intermediate Variable for improved solving

OMEGADENOM(T) Denominator of Omega

* Variables for pivot and shift.

Alpha(T) Pivot

b(T) Shift

HALFMAC(T) Marginal Cost of half abatement (anchor point for b)

* Define the size of the market for clean energy

CleanDemand(T) Demand for clean energy

* Variables for solar

SolTechPrice(T) Price of solar technology dollars per kWh

SolNetPrice(T) Solar price net of technology and integration costs

SOLPriceDenom(T) Intermediate variable for solar price

SolDemand(T)   Demand for solar in kWh

SolDemandRat(T) Intermediate variable solar demand ratio

SolShare(T)   Actual Market Share of Solar

SolBase   Base share weight

SolIntMult(T)

SolIntCost(T)   Cost of grid integration

Backup(t)

* Variables for the balance of the market

BOMPriceFact(T)

BOMPriceDenom(T)

BOMDemand(T)

BOMDemandrat(T)

BOMShare(T)

BOMLogit(T)

BOMPriceA(T)   Dummy Variable to report BomPrice

Theta1A(T)   Dummy Variable to report backstop Price;

POSITIVE VARIABLES MIU, TATM, TOCE, E, MAT, MATAV, MU, ML, Y, YGROSS, C, K, I, CCA, PI, Lambda, Omegamax, Halfmac, SolPrice, SolNetPrice, SolPriceDenom, SolShare;

EQUATIONS

CCTFIRST(T)	First period cumulative carbon
CCACCA(T)	Cumulative carbon emissions
UTIL	Objective function
YY(T)	Output net equation
YNETEQ(T)	Output net of damages equation
YGROSSEQ(T)	Output gross equation
DAMEQ(T)	Damage equation
ABATEEQ(T)	Cost of emissions reductions equation
CC(T)	Consumption equation
KK(T)	Capital balance equation
KK0(T)	Initial condition for capital
KC(T)	Terminal condition for capital
CPCE(t)	Per capita consumption definition
PCYE(T)	Per capita income definition
EE(T)	Emissions equation
SEQ(T)	Savings rate equation
RIEQ(T)	Interest rate equation
FORCE(T)	Radiative forcing equation
MMAT0(T)	Starting atmospheric concentration
MMAT(T)	Atmospheric concentration equation
MMATAVEQ(t)	Average concentrations equation

MMU0(T)　　Initial shallow ocean concentration

MMU(T)　　Shallow ocean concentration

MML0(T)　　Initial lower ocean concentration

MML(T)　　Lower ocean concentration

TATMEQ(T)　　Temperature-climate equation for atmosphere

TATM0EQ(T)　　Initial condition for atmospheric temperature

TOCEANEQ(T)　　Temperature-climate equation for lower oceans

TOCEAN0EQ(T)　　Initial condition for lower ocean temperature

PERIODUEQ(t)　　Instantaneous utility function equation

* Equations for syncronizing notation with Balance

PIEQ(T)　　Participation Cost Markup

OMEGAEQ(T)　　Damage Equation

LAMBDAEQ(T)　　Abatement cost as a proportion of output

* Intermediate Variables for improved solving

OMEGADENOMEQ(T)　Denominator of Omega

* New equations

AlphaEQ(T)　　Pivot

bEQ(T)　　Shift

HALFMACEQ(T)　　Marginal cost of half abatement

* Define the size of the market for clean energy

CleanDemandEQ(T) Equation for demand of clean energy

SolTechPriceF(T) First period solar price

*SolTechPriceS(T) Second period solar price

SolTechPriceEQ(T) Solar technology price

SolNetPriceEQ(T) Solar price net of technology and integration cost

SolPriceDenomEQ(T) Intermediate variable for solar price

SolDemandEQ(T) Demand for solar

SolDemandRatEQ(T) Intermediate variable for solar demand ratio

SolShareEQ(T) Actual share of solar

SolIntMultEQ(T) Multiplier for solar integration cost

SolIntCostEQ(T)

BackupEQ(T)

BOMDemandEQ(T) Demand for BOM in kWh

BOMShareEQ(T) Market share of BOM

BomPriceAEQ(T)

MiuEQ(T)

Theta1AEQ(T) Dummy Variable to report theta1;

** Equations of the model

CCTFIRST(TFIRST).. CCA(TFIRST)=E=0;

```
CCACCA(T+1)..     CCA(T+1)=E=CCA(T)+ E(T);

KK(T)..           K(T+1) =L= (1-DK)**10 *K(T)+10*I(T);

KK0(TFIRST)..     K(TFIRST) =E= K0;

KC(TLAST)..       .02*K(TLAST) =L= I(TLAST);

EE(T)..           E(T)=E=10*SIGMA(T)*(1-MIU(T))*YGROSS(T) + ETREE(T);

* Replaced ln(2) with .69315 in Force equation for improved solving

FORCE(T)..                    FORC(T)                    =E=
    FCO22X*((log((Matav(T)+.000001)/596.4)/.69315))+FORCOTH(T);

MMAT0(TFIRST)..   MAT(TFIRST) =E= MAT2000;

MMU0(TFIRST)..    MU(TFIRST)  =E= MU2000;

MML0(TFIRST)..    ML(TFIRST)  =E= ML2000;

MMAT(T+1)..       MAT(T+1)    =E= MAT(T)*b11+MU(T)*b21 + E(T);

MMATAVEQ(t)..     MATAV(T)    =e= (MAT(T)+MAT(T+1))/2;

MML(T+1)..        ML(T+1)     =E= ML(T)*b33+b23*MU(T);

MMU(T+1)..        MU(T+1)     =E= MAT(T)*b12+MU(T)*b22+ML(T)*b32;

TATM0EQ(TFIRST).. TATM(TFIRST) =E= TATM0;

TATMEQ(T+1)..     TATM(T+1) =E= TATM(t)+C1*(FORC(t+1)-LAM*TATM(t)-
    C3*(TATM(t)-TOCEAN(t)));

TOCEAN0EQ(TFIRST).. TOCEAN(TFIRST) =E= TOCEAN0;

TOCEANEQ(T+1)..        TOCEAN(T+1)   =E=   TOCEAN(T)+C4*(TATM(T)-
    TOCEAN(T));

YGROSSEQ(T)..   YGROSS(T) =e= AL(T)*L(T)**(1-GAMA)*K(T)**GAMA;

DAMEQ(T)..      DAMAGES(t) =E= YGROSS(T)- YGROSS(T)*OMEGA(T);
```

```
YNETEQ(T)..     YNET(T) =E=  YGROSS(T)*OMEGA(T);

AbateEQ(T)..    Abatecost(T) =E= Lambda(T)*Ygross(T);

YY(T)..         Y(T) =E= YGROSS(T)*(1-LAMBDA(T))*OMEGA(T);

SEQ(T)..        S(T)    =E= I(T)/(Y(T)+.001);

RIEQ(T)..       RI(T)   =E= GAMA*Y(T)/K(T)- (1-(1-DK)**10)/10;

CC(T)..         C(T)    =E= Y(T)-I(T);

CPCE(T)..       CPC(T)  =E= C(T)*1000/L(T);

PCYE(T)..       PCY(T)  =E= Y(T)*1000/L(T);

PERIODUEQ(T)..  PERIODU(T) =E= ((C(T)/L(T))**(1-ELASMU)-1)/(1-
    ELASMU);

UTIL..          UTILITY =E= SUM(T, 10 *RR(T)*L(T)*(PERIODU(T))/scale1)+
    scale2;


* Intermediate Variables for Improved Solving

OMEGADENOMEQ(T)..  OMEGADENOM(T) =E= 1+aa1*TATM(T)+
    aa2*TATM(T)**aa3;

* Added to syncronize notation with Balance.

PIEQ(T)..       PI(T) =E= PARTFRACT(T)**(1-THETA2);

OMEGAEQ(T)..    OMEGA(T) =E= 1/OMEGADENOM(T);

LAMBDAEQ(T)..   LAMBDA(T) =E= max[(1-
    Alpha(T))*PI(T)*((THETA1(t)*MIU(T)**THETA2)-(b(T)*.045*miu(t))),0];
```

```
* Equations for pivot and shift

*AlphaEQ(T)..     Alpha(T) =E= Alpha0;  (used for baseline and max runs)

AlphaEQ(T)..     Alpha(T) =E= .0875/exp(3.454*(SolNetPrice(T)/SolPrice0));


*bEQ(T)..        b(T) =E= b0;  (used for baseline and max runs)

bEQ(T)..        b(T) =E= .0548/exp(3.646*(SolNetPrice(T)/SolPrice0));


HALFMACEQ(T)..  HALFMAC(T) =E= THETA2*THETA1(t)*.5**(THETA2-1);


* Equation for the size of the market

CleanDemandEQ(T)..      CleanDemand(T) =E= Tau(T)*miu(T)*ygross(T);


* Initial Conditions

SolTechPriceF(Tfirst).. SolTechPrice(Tfirst) =E= SolPrice0;

*SolTechPriceS(TSecond).. SolTechPrice(TSecond) =E= SolPrice2;


MiuEQ(T)..              Miu(T) =G= Miu(T-1);


* Variables used for troubleshooting - not part of model

BackupEQ(T)..           Backup(T) =E= Backprice(T);

BomPriceAEQ(T)..        BomPriceA(T) =E= BomPrice(T);

Theta1AEQ(T)..          Theta1A(T) =E= Theta1(T);
```

```
* Intermediate variables

SolDemandRatEQ(T+1)..                    SolDemandRat(T+1)      =E=
    max[1,(SOLdemand(T+1)/SOLdemand(T))];

SolPriceDenomEQ(T+1)..                   SolPriceDenom(T+1)      =E=
    SolDemandRat(T+1)**SolRTSFact;

SolIntMultEQ(T)..        SolIntMult(T)  =E=  ((1-(1/[1+exp{min(50*(SolShare(T)-
    FullBack),15)}])));


SOLTechPriceEQ(T+1)..                    SOLtechPrice(T+1)       =E=
    SOLtechPrice(T)/SolPriceDenom(T+1);

SolDemandEQ(T+1)..     SolDemand(T+1) =E= SolShare(T+1)*CleanDemand(T+1);

*SolShareEQ(T+1)..                              SolShare(T+1)      =E=
    (1/exp((solnetprice(T+1)/BomPrice(T+1))**Solvar))/((1/exp(BomVar))+exp((sol
    netprice(T+1)/BomPrice(T+1))**Solvar));

SolShareEQ(T+1)..                               SolShare(T+1)      =E=
    (1/solnetprice(T+1)**Solvar)/((1/BomPrice(T+1)**BomVar)+(1/solnetprice(T+1
    )**Solvar));


SolIntCostEQ(T)..     SolIntCost(T) =E= BackPrice(T)*SolIntMult(T);

*SolIntCostEQ(T)..     SolIntCost(T) =E= 0;

SolNetPriceEQ(T+1)..    SolNetPrice(T) =E= SolTechPrice(T)+SolIntCost(T);
```

```
BOMDemandEQ(T+1)..          BOMDemand(T+1)   =E=   CleanDemand(T+1)-
    SolDemand(T+1);
BOMShareEQ(T)..     BOMShare(T) =E= 1-SOLShare(T);


* Specify starting point and lower limits for theoretical consistency and solvability
Omegadenom.lo(T) = 1;
SolDemandRat.lo(T) = 1;
SolDemand.lo(T)=.00005;
*SolDemand.lo(T)= 1;
SolPriceDenom.lo(T) = 1;
SolNetPrice.up(T) = 400;
SolNetPrice.lo(T) = .01;
*BomPrice.lo(T) = .01;


Miu.l("3")=0.18383;
Miu.l("4")=0.21134;
Miu.l("5")=0.24047;
Miu.l("6")=0.27112;
Miu.l("7")=0.30331;
Miu.l("8")=0.33713;
Miu.l("9")=0.37271;
Miu.l("10")=0.41016;
Miu.l("11")=0.44962;
```

```
Miu.l("12")=0.49133;

Miu.l("13")=0.53559;

Miu.l("14")=0.58272;

Miu.l("15")=0.63301;

Miu.l("16")=0.68679;

Miu.l("17")=0.7444;

Miu.l("18")=0.80618;

Miu.l("19")=0.87242;

Miu.l("20")=0.94315;

Miu.l("21")=1;

Miu.l("22")=1;

Miu.l("23")=1;

Miu.l("24")=1;

Miu.l("25")=1;

Miu.l("26")=1;

Miu.l("27")=1;

Miu.l("28")=1;

Miu.l("29")=1;

Miu.l("30")=1;

Miu.l("31")=1;

Miu.l("32")=1;

Miu.l("33")=1;

Miu.l("34")=1;
```

```
Miu.l("35")=1;

Miu.l("36")=1;

Miu.l("37")=1;

Miu.l("38")=1;

Miu.l("39")=1;

Miu.l("40")=1;

Miu.l("41")=1;

Miu.l("42")=1;

Miu.l("43")=1;

Miu.l("44")=1;

Miu.l("45")=1;

Miu.l("46")=1;

Miu.l("47")=1;

Miu.l("48")=1;

Miu.l("49")=1;

Miu.l("50")=1;

Miu.l("51")=1;

Miu.l("52")=1;

Miu.l("53")=1;

Miu.l("54")=1;

Miu.l("55")=1;

Miu.l("56")=1;

Miu.l("57")=1;
```

```
Miu.l("58")=1;
Miu.l("59")=1;
Miu.l("60")=1;

**  Upper and Lower Bounds: General conditions for stability

K.lo(T)         = 100;
MAT.lo(T)       = 10;
MU.lo(t)        = 100;
ML.lo(t)        = 1000;
C.lo(T)         = 20;
TOCEAN.up(T)    = 20;
TOCEAN.lo(T)    = -1;
TATM.up(t)      = 20;
miu.up(t)       = LIMMIU;

partfract("1")= 0.25372;

* First period predetermined by Kyoto Protocol. In original DICE, dropped for solvability
*miu.fx("1")     = 0.005;

** Fix savings assumption for standardization if needed
```

```
s.fx(t)=.22;

** Cumulative limits on carbon use at 6000 GtC
CCA.up(T) = FOSSLIM;

** Solution options
option iterlim = 4000;
option reslim = 99999;
option solprint = on;
option limrow = 100;
option limcol = 100;

model CO2 /all/;
CO2.optfile = 1;

* Call definition files for individual runs
*$include def_D2RTS15.gms
*$include def_D2RTS20.gms
*$include def_D2RTS25.gms

$include def_D3RTS15.gms
*$include def_D3RTS20.gms
*$include def_D3RTS25.gms
```

```
*$include def_D4RTS15.gms
*$include def_D4RTS20.gms
*$include def_D4RTS25.gms
```

Sample Definition File

The final lines of the model above call definition files. Definition files are specific to each model run and contain the RTS factor for each run, specific instructions about how many solve iterations to use, and code to give each input file the appropriate name. Note that “SolPrice2” is a legacy parameter from a development version of the model and is not used in the final model. SolRTSFact is the exponent necessary to achieve the desired percent reduction in cost per doubling in scale. The example below is the definition file for the low scenario, the SolRTSFact parameters are .3219 and .4150 for the medium and high scenarios, respectively.

```
SolPrice2 =  155.01;
SolRTSFact = .2345;

solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
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solve CO2 maximizing UTILITY using dnlp ;

*$ontext
solve CO2 maximizing UTILITY using dnlp ;
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solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
solve CO2 maximizing UTILITY using dnlp ;
```

solve CO2 maximizing UTILITY using dnlp ;

solve CO2 maximizing UTILITY using dnlp ;

Parameters

Year(t) Date

D3RTS15_SOLPrice(T)

D3RTS15_SolShare(T)

D3RTS15_SolDemand(T)

D3RTS15_BOMPrice(T)

D3RTS15_BOMShare(T)

D3RTS15_BOMDemand(T)

D3RTS15_alpha(T)

D3RTS15_b(T)

D3RTS15_y(t)

D3RTS15_cpc(t)

D3RTS15_s(t)

D3RTS15_indem(t)

D3RTS15_sigma(t)

D3RTS15_tatm(t)

D3RTS15_mat(t)

D3RTS15_tax(t)

D3RTS15_ri(t)

D3RTS15_rr(t)

D3RTS15_al(t)

D3RTS15_forcoth(t)

D3RTS15_l(t)

D3RTS15_etree(t)

D3RTS15_yy(t)

D3RTS15_cc(t)

D3RTS15_miu(t)

D3RTS15_wem(t)

D3RTS15_ri(t)

D3RTS15_dam(t)

D3RTS15_abate(t)

D3RTS15_mcemis(t)

D3RTS15_utility

D3RTS15_alpha(t)

D3RTS15_b(t)

D3RTS15_Damages(T)

D3RTS15_Abate(T)

D3RTS15_CleanDemand(T)

```
D3RTS15_SolShare(T)

D3RTS15_SolDemand(T)

D3RTS15_SolTechPrice(T)

D3RTS15_SolIntCost(T)

D3RTS15_solIntMult(T)

D3RTS15_SolNetPrice(T)

D3RTS15_Backup(T)

D3RTS15_BomDemand(T)

D3RTS15_BOMShare(T)

D3RTS15_BOMPriceA(T)

D3RTS15_Theta1A(T);


Year(t)         = 2005 +10*(ord(t)-1);

D3RTS15_y(t)=y.l(t);

D3RTS15_cpc(t)=cpc.l(t);

D3RTS15_s(t)=s.l(t)     ;

D3RTS15_indem(t)= e.l(t)-etree(t);;

D3RTS15_sigma(t)=sigma(t) ;

D3RTS15_tatm(t)=tatm.l(t)  ;

D3RTS15_mat(t)=mat.l(t)     ;

D3RTS15_tax(t)=-1*ee.m(t)*1000/(kk.m(t)+.00000000001)       ;

D3RTS15_ri(t)=ri.l(t);

D3RTS15_rr(t)=rr(t)   ;
```

```
D3RTS15_al(t)=al(t)    ;
D3RTS15_forcoth(t)=forcoth(t);
D3RTS15_l(t)=l(t);
D3RTS15_etree(t)=etree(t);
D3RTS15_yy(t)=yy.m(t)     ;
D3RTS15_cc(t)=cc.m(t)      ;
D3RTS15_miu(t)=miu.l(t)     ;
D3RTS15_wem(t)= e.l(t);
D3RTS15_ri(t)=ri.l(t)         ;
D3RTS15_dam(t)= damages.l(t);
D3RTS15_abate(t) = abatecost.l(t);
*D3RTS15_mcemis(t)=                        THETA2*THETA1(t)*miu.l(t)**(THETA2-1)/sigma(t)*1000;
D3RTS15_utility=utility.l        ;
D3RTS15_alpha(t)=alpha.l(t);
D3RTS15_b(t)=b.l(t);
*D3RTS15_Damages(T)=damages.l(t);
D3RTS15_Abate(T)=abatecost.l(T);
D3RTS15_CleanDemand(T)=cleandemand.l(t);
D3RTS15_SolShare(T)=solshare.l(T);
D3RTS15_SolDemand(T)=soldemand.l(T);
D3RTS15_SolTechPrice(T)=soltechprice.l(T);
D3RTS15_SolIntCost(T)=solintcost.l(T);
```

```
D3RTS15_SolIntMult(T)=solintmult.l(T);
D3RTS15_SolNetPrice(T)=solnetPrice.l(T);
D3RTS15_Backup(T)=backup.l(T);
D3RTS15_BomDemand(T)=bomdemand.l(T);
D3RTS15_BOMShare(T)=bomshare.l(T);
D3RTS15_BOMPriceA(T)=bompricea.l(T);
D3RTS15_Theta1A(T)=Theta1A.l(T);



File D3RTS15;
D3RTS15.pc=6;
D3RTS15.pw=1000;
Put D3RTS15;
Put / "Optimal run (economic optimum)";
Put / "year";
Loop (T, put year(T)::0);

Put / "Abatement";
Loop (T, put D3RTS15_Miu(T)::5);

Put / "Pivot";
Loop (T, put D3RTS15_Alpha(T)::4);
```

```
Put / "Shift";
Loop (T, put D3RTS15_b(T)::4);

Put / "Damages";
Loop (T, put D3RTS15_Dam(T)::3);

Put / "Abatement Cost";
Loop (T, put D3RTS15_Abate(T)::4);

Put / "Clean Demand";
Loop (T, put D3RTS15_CleanDemand(T)::3);

Put / "Solar Share";
Loop (T, put D3RTS15_SolShare(T)::4);

Put / "Solar Demand";
Loop (T, put D3RTS15_SolDemand(T)::5);

Put / "Solar Tech Price";
Loop (T, put D3RTS15_SolTechPrice(T)::3);

Put / "Solar Integration Cost";
Loop (T, put D3RTS15_SolIntCost(T)::4);
```

```
Put / "Solar Integration Cost Multiplier";

Loop (T, put D3RTS15_SolIntMult(T)::5);


Put / "Solar Net Cost";

Loop (T, put D3RTS15_SolNetPrice(T)::3);


Put / "Backup Cost";

Loop (T, put D3RTS15_Backup(T)::3);


Put / "BOM Demand";

Loop (T, put D3RTS15_BomDemand(T)::4);


Put / "Bom Share";

Loop (T, put D3RTS15_BOMShare(T)::4);


Put / "Bom Price";

Loop (T, put D3RTS15_BOMPriceA(T)::3);


Put / "BackStop price";

Loop (T, put D3RTS15_Theta1A(T)::5);


Put / "output";
```

```
Loop (T, put D3RTS15_y(T)::3);

Put / "pccon";

Loop (T, put D3RTS15_cpc(T)::3);

Put / "savrate";

Loop (T, put D3RTS15_s(T)::4);

Put / "indem";

Loop (T, put D3RTS15_indem(T)::4);

Put / "sigma";

Loop (T, put D3RTS15_sigma(T)::4);

Put / "temp";

Loop (T, put D3RTS15_tatm(T)::3);

Put / "conc";

Loop (T, put D3RTS15_mat(T)::3);

Put / "soc cost carbon";

Loop (T, put D3RTS15_tax(T)::2);

Put / "intrate";

Loop (T, put D3RTS15_ri(T)::3);

Put / "discrate";

Loop (T, put D3RTS15_rr(T)::5);

Put / "prod";

Loop (T, put D3RTS15_al(T)::5);

Put / "exogforc";

Loop (T, put D3RTS15_forcoth(T)::3);
```

```
Put / "pop";

Loop (T, put D3RTS15_l(T)::3);

*Put / "carbon tax";

*Loop (T, put D3RTS15_mcemis(T)::4);

Put / "margy";

Loop (T, put D3RTS15_yy(T)::3);

Put / "margc";

Loop (T, put D3RTS15_cc(T)::5);

Put / "miu";

Loop (T, put D3RTS15_miu(T)::3);

Put / "total emissions";

Loop (T, put D3RTS15_wem(T)::3);

Put / "interest rate";

Loop (T, put D3RTS15_ri(T)::4);

Put / "damages";

Loop (T, put D3RTS15_dam(T)::3);

Put / "abatement cost";

Loop (T, put D3RTS15_abate(T)::2);

Put /"objective function";

Put D3RTS15_utility::3;
```

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