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Analysis of the Impact of Technological Change on the Cost of Achieving Climate Change Mitigation Targets

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ANALYSIS OF THE IMPACT OF TECHNOLOGICAL CHANGE ON THE COST OF ACHIEVING CLIMATE CHANGE MITIGATION TARGETS

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DEDICATION

To Bill and his many friends.

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Reflecting back upon my graduate school experience has highlighted the depth of support and assistance I’ve received throughout my long journey. Graduate school has been an amazing, exhilarating, and at times arduous experience. I could not have succeeded without the support of my friends, family, mentors, and peers.

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ABSTRACT

ANALYSIS OF THE IMPACT OF TECHNOLOGICAL CHANGE ON THE COST OF ACHIEVING CLIMATE CHANGE MITIGATION TARGETS

SEPTEMBER 2015

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There is widespread consensus that low carbon energy technologies will play a key role in the future global energy system. Many of the low-carbon technologies under consideration are not yet commercially available, and their ultimate value depends on a host of deeply uncertain socioeconomic, environmental, and technological considerations. While it is clear that significant investment in the energy system is needed, the optimal allocation of these investments is unclear.

This dissertation develops a methodology for (1) analyzing the impact of low carbon energy technologies on the cost of meeting emission reduction targets (policy cost) and (2) using this information to develop optimal R&D investment portfolios. We then apply this methodology to analyze the value of low carbon energy R&D across two key dimensions of uncertainty and two theoretical models.

In the first part we apply a set of expert-elicitation derived future technology scenarios to the Global Change Assessment Model and conduct a large ensemble of model runs. We then use the results of these runs to develop our methodology for analyzing the impact of technological change in low carbon energy technologies on policy cost.

The second part builds on the methodology of part one by adding probabilistic information to the analysis. This allows us to not only measure the impact of technological change on policy costs, but also to derive optimal R&D investment portfolios. We conduct a sensitivity analysis of our results across assumptions about the structure of the demand side of the energy system.

In the third part we consider the influence of model choice on our results. We apply harmonized input assumptions to two different integrated assessment models and examine how the model outputs differ.

We find that although the impacts of low carbon energy technologies vary widely across different scenarios of socioeconomic and technological development, as well as across the models used for the analysis, the optimal R&D investment portfolios are surprisingly robust. We also find that return to R&D investment is sharply decreasing.

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INTRODUCTION

1.1. Motivation

Climate change is arguably the most significant and pervasive issue facing humanity in the 21st Century. The Intergovernmental Panel on Climate Change (IPCC), in the Summary For Policy Makers of the Fifth Assessment Report (IPCC 2014), describes the evidence for, and risks of, climate change in unambiguous terms: *"Human influence on the climate system is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history…Recent climate changes have had widespread impacts on human and natural systems…Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia…Continued emission of greenhouse gases will cause further warming and long-lasting changes in all components of the climate system, increasing the likelihood of severe, pervasive and irreversible impacts for people and ecosystems."*

The IPCC is equally unambiguous about the necessary action: *"Limiting climate change would require substantial and sustained reductions in greenhouse gas emissions which, together with adaptation, can limit climate change risks."* (IPCC 2014). Similar sentiments are echoed across the scientific community. In addition to the IPCC, the Global Energy Assessment (GEA) (GEA 2012a), the Stern Review (Stern 2007), and many other studies have all called for sharp reductions of carbon emissions during the 21^{st} century.

Reducing CO2 emissions is far more easily said than done. CO2 emissions come from many sources: in addition to energy, land use, buildings, and industry also have significant impacts on emissions (IPCC 2014). These emission drivers are influenced by socioeconomic factors such as population and GDP, which are in turn affected by feedbacks from activity in the energy, land use, and industrial sectors. Finally, emissions reductions can be achieved in any number of ways, from energy efficiency, to low carbon energy sources, to atmospheric capture, which are also subject to feedbacks.

The policy maker's problem is further compounded by deep uncertainty about the problem. That is, there is not just a stochastic uncertainty about the value of the parameters of the system, but also uncertainty about the proper structure of the conceptual model, the probability distributions of the model parameters, and/or the desirability of alternative outcomes (Lempert, Popper & Bankes 2003).

Integrated Assessment (IA) has emerged as one of the main techniques of climate policy research. IA considers the technological, environmental, and socioeconomic aspects of the climate change problem holistically, from a systems perspective. The primary tool of IA is the Integrated Assessment Model (IAM). IAMs concurrently model the socioeconomic, technological and climatological systems that affect climate change, thereby allowing researchers to study the problem from a systems perspective.

IAMs have been widely used to evaluate climate change mitigation policies and have supported many prominent studies of climate change, including the Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report (IPCC 2014), the Global Energy Assessment (GEA 2012a), and many others.

Multiple IA studies have indicated that Low Carbon Energy Supply (LCES) technologies such as solar, wind, bioenergy, and carbon capture will be needed to meet emissions targets at a reasonable cost (or at all) (GEA 2012a, IPCC 2014). However, many such technologies are not yet commercially available. One response to this need is public-sector research and development (R&D) into LCES technologies[1].

R&D has been found to be cost-effective (Corderi, Lin 2011), but the nature of climate change complicates the R&D allocation problem. R&D has no guarantee of success, and even if successful, each potential LCES technology will have a different impact on emissions, and the relative value of such emissions reductions will in turn depend on the underlying technological, socioeconomic and environmental scenarios.

Thus, the policy maker seeking to promote the development of LCES technologies is faced with the daunting task of investing R&D funds today to minimize the future risks of climate change without knowing for certain how those investments will impact LCES technologies, or how LCES technologies, if successful, would impact the cost of emissions reductions (abatement). Moreover, the stringency of the climate target (and therefore the demand for abatement), the future demand for energy, the sensitivity of the climate to emissions, the magnitude of damages due to warming, and a host of other key parameters and variables are all deeply uncertain.

1.2. Objectives

This dissertation addresses the question of how to allocate R&D investments into LCES technologies in the face of these deep uncertainties. The central objective of this dissertation is to develop an analytical framework to explore the impact of LCES technologies on climate change mitigation costs ("mitigation costs"), and to apply this framework to explore the policy implications of such impacts. Our approach is to follow

[1] Unless otherwise stated, we use the term "R&D" to refer specifically to supply-side R&D.

the Long Term Policy Analysis (LTPA) methodology described in Lempert et al. (2003) and more fully explained in Section 1.3.2.

This dissertation is organized as follows: the balance of this chapter provides a review of the relevant literature. Chapter 2 develops our methodology for characterizing the potential impact of low carbon technologies and applies it to a menu of LCES technologies. Chapter 3 extends the methodology of Chapter 2 to include policy decisions (R&D allocations). In Chapter 4 we examine the impact of different models on the results. Finally, Chapter 5 summarizes our conclusions and proposes future work.

1.3. Literature Review

1.3.1. Integrated Assessment Models

Integrated assessment models address the interdependencies between climate and energy systems. IAMs vary widely in their architecture and purpose, but they all connect an economic model with a climate model in order to study the interactions between climate and energy.

Carbon policies can be implemented directly in IAMs by specifying a carbon tax or emissions cap, or implicitly by constraining some variable affected by carbon emissions, such as CO2 concentration or radiative forcing. In this work we implement carbon policy as a radiative forcing constraint, which implies a carbon price.

IAMs can be broadly grouped into two classes: top-down models that optimize highly aggregated models of climate and economic systems, and bottom-up models that simulate areas of the economy in greater detail. In this dissertation we use two IAMs: the Global Change Assessment Model (GCAM), and the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE). We discuss these models in detail in sections 2.1.3 and 3 respectively and devote chapter 4 of this dissertation to a comparison of the two models. Here, we provide a general overview of IAMs.

IAMs can be categorized in terms of their equilibrium concept, solution dynamics, time horizon, and technological and environmental detail (Kriegler et al. 2015a, Kriegler et al. 2015b). Each of these qualities has important implications for the model's behavior.

Perhaps the most important characteristic is the equilibrium concept. Partial equilibrium models describe a narrow area of the economy in detail while treating large swaths of the economy exogenously. General equilibrium models simulate the economy broadly but offer limited detail in individual sectors (Kriegler et al. 2015a).

IAMs can also optimize intertemporaly or recursive-dynamically. Recursive-dynamic models solve each period sequentially. Intertemporal optimization models can be used to study the dynamics of investment in production capital, but sacrifice detail due to the computational intensity of intertemporal optimization. The tradeoffs between these solution concepts are the subject of some debate. One study (Babiker et al. 2009) noted that while intertemporal optimization models allow more options to adjust to policy constraints – and consequently lower macroeconomic costs, recursive dynamic models produce similar behavior in the energy sector and allows for greater flexibility in modeling the energy sector.

Another important consideration is the level of technological and environmental detail. Most bottom-up IAMs provide a high level of technological detail in the low carbon energy sector. Many models link with simplified climate models such as the Model for the Assessment of Greenhouse-gas Induced Climate Change (MACICC)

(Meinshausen, Raper & Wigley 2011) to provide climate change impact data. Land use is particularly important in IA because land use has a strong impact on greenhouse gas emission in its own right, and bioenergy technologies compete in the energy sector for market share and the agricultural sector for arable land.

In this exercise GCAM and MESSAGE were chosen because they both have high levels of detail in the energy sector, but different equilibrium and solution concepts. GCAM is a partial equilibrium, dynamic-recursive model and MESSAGE-MACRO is a general equilibrium, intertemporal optimization model. Choosing models with different structures offers us the opportunity to compare how modeling factors such as equilibrium and solution concept affect our results.

1.3.2. Long Term Policy Analysis

The deep uncertainty and long time horizons of climate policy analysis place it within the class of problems termed Long Term Policy Analysis (LTPA) by Lempert, et al. (2003). Lempert defines the aim of LTPA as *"identifying, assessing, and choosing among near-term actions that shape options available to future generations"* and identifies four key elements of successful LTPA: (1) large ensembles of scenarios, (2) seeking of robust (as opposed to optimal) strategies, (3) adaptability, and (4) provision for interactive exploration of plausible futures.

In this dissertation we will develop a methodology informed by these principles. We will use probabilistic data and sensitivity analysis to analyze the impact of R&D investment into LCES technologies. Our methodology includes an innovative application of importance sampling to reduce the computational sensitivity and improve the adaptability of our analysis (see section 3.2.5 for details).

1.3.3. Technological Change

Technological change has been described as *"a change in the character of productive activity"* (Wing 2006). Wing, drawing on the seminal work of (Schumpeter 1950), identifies three drivers of technological change: invention, whereby new technologies are developed; innovation, the process of commercializing such new technologies; and the diffusion of these technologies into the economy.

The concept of technological change was first noted in the 19th century by Bryan & Harter (1899). Hicks (1932) hypothesized that technological change was driven by cost-minimizing firms economizing on the costliest factors of production; he termed this process Induced Technological Change (ITC). The theory of ITC was further refined by Wright (1936), Arrow (1962), and many others.

1.3.4. Expert Elicitation

The phenomenon of technological change has been well documented, however, predicting the impact of ITC is an uncertain process at best. There is no way to predict what breakthroughs will occur as a result of invention, what innovations these inventions will produce, and how these innovations will diffuse through the economy. Methods such as learning and experience curves provide some insight, but have important weaknesses (Nordhaus 2013) and require information about past performance[2]. Since many of the technologies being considered as alternatives to fossil fuels do not yet exist in commercial form, there is no past performance upon which to base an estimate.

[2] In this dissertation we will frequently use the term "performance" rather than a parameter's absolute value. We do this to avoid confusion between cost parameters (where a lower value indicates higher performance) and efficiency parameters (where higher values indicate higher performance). In all cases an improvement in performance is a movement in the direction of improvement.

The inherent uncertainty associated with technological change is a key issue for energy policy research because the future performance of both supply and demand side technologies has large impacts on the energy system and the larger economy. In order to address this issue the National Research Council of the U.S. National Academy of Sciences has recommended the use of expert elicitation data in its R&D funding decisions (National Research Council 2007).

Expert elicitation is a method of obtaining estimates of future technological performance based on expert judgement. One early proponent of expert elicitation was Raiffa (1968), who advocated for using subjectively generated “judgmental probabilities” about vague but relevant uncertainties to inform decision making. In order to obtain the highest quality results, the elicitation process is designed with human cognitive characteristics in mind (von Winterfeldt, Edwards 1986). Important aspects of elicitation development include designing the elicitation to present the experts with cognitively simple assessment questions and minimize the impact of decision biases. Consistency checks are also incorporated to identify potential issues such as unaccounted-for bias.

The process of expert elicitation can be applied to a wide spectrum of problems. In this work we are concerned specifically with R&D investment. Sharpe & Keelin (1998) outlined a standard process for R&D portfolio elicitations. First, a precise definition of success is developed for each potential R&D project. Next, experts assess each project and generate a subjective probability of success across a number of specific funding levels. This information is then used as an input to a model that calculates the ultimate value of the success. This information is then used to prioritize R&D projects.

Baker et al. (2007) notes that assessing climate change technologies poses several additional challenges. Foremost among these is that the ultimate value of low carbon energy depends in large part on the severity of climate damages. The severity of climate damages affects not only the overall value of low carbon energy, but also the value of technologies relative to each other. For example, if damages are mild (and optimal abatement is low), incremental improvements in coal technology may be more valuable than improvements in solar, but if damages are severe (with correspondingly high abatement), solar may be very valuable while coal is unattractive at any price.

Another complication of energy R&D is the prospect of substitutability between technologies. Most proposed replacements for fossil fuel technologies produce electricity and many of these technologies are substitutes, meaning that a breakthrough in one technology might negate the impact of breakthroughs in other technologies.

Elicitations have been used extensively in energy policy research. Recent studies have elicited Carbob Capture and Storage (CCS) (Baker, Chon & Keisler 2009b, Chan et al. 2011a), nuclear (Baker, Chon & Keisler 2008, Anadon et al. 2013), solar (Baker, Chon & Keisler 2009a), and alternative fueled vehicles (Bosetti et al. 2011b, Bosetti et al. 2011a), among others. These studies have provided valuable insight and have contributed to a growing body of elicitation data; however, they have considered a single technology. This has limited the insights they can offer about the interdependencies between technologies.

A logical evolution of single technology elicitation studies is to analyze multiple technologies simultaneously. Multi-technology assessments will address the environmental and technological interdependency issues; however, such assessments will require elicitations of multiple technologies, as well as a modeling platform capable of modeling the environmental and technological interdependencies of the climate change problem. As discussed in section 1.3.1, integrated assessment models provide the modeling platform, but they require detailed inputs for multiple technologies.

One approach to the need for multi-technology elicitations would be to elicit multiple technologies simultaneously. This would result in compatible elicitations, however the time, expense, and breadth of expertise required makes such an exercise impractical. Another option is to aggregate existing elicitation data. While aggregation is a more practical option, it poses challenges of its own: elicitations are generally designed with one specific application in mind, so different elicitations often have significantly different assumptions that require considerable effort to harmonize.

This dissertation uses the output of one such elicitation aggregation exercise, the Technology Elicitations and Modeling (TEaM) project. We discuss the background of TEaM in section 2.1.2 below. Baker et al. (2015) provides a detailed overview of the aggregation process.

CHAPTER 2

THE DIFFERENTIAL IMPACT OF LOW CARBON ENERGY SUPPLY TECHNOLOGIES ON CLIMATE CHANGE MITIGATION COST UNDER A RANGE OF SOCIOECONOMIC SCENARIOS[3]

2.1. Introduction

Climate change is widely recognized as a serious problem, and there is widespread consensus that substantial reductions in CO2 emissions during the 21st century must be an integral part of addressing climate change (IPCC 2014). Consequently, low carbon energy technologies will play a key role in the future global energy system. While it is clear that significant investment in the energy system is needed (Riahi et al. 2012, McCollum et al. 2013, Lemoine, McJeon 2013), the path to the future energy system, as well as the policies that will facilitate the transition, are unclear. Many of the low-carbon technologies under consideration are not yet commercially available (e.g. Carbon Capture and Sequestration (CCS)), while others such as nuclear are subject to non-technical considerations such as public opposition and proliferation concerns which may drive up costs, or prevent the adoption even if the technology is otherwise cost competitive. At the same time, the future population and GDP of the world will strongly affect the demand for energy and the availability of resources for adaptation and mitigation efforts, which may in turn affect the optimal climate policy.

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[3] Reprinted from *Energy Policy*, Vol. 80, Robert Barron, Haewon McJeon, The differential Impact of low-carbon technologies on climate change mitigation cost under a range of socioeconomic and climate policy scenarios, Pages 264-274., Copyright 2015, with permission from Elsevier under license number 3641480197627.

One near term response to the need for low-carbon energy is public-sector research and development (R&D) into low-carbon energy supply technologies (supply-side R&D[4]). R&D has been found to be cost-effective (Corderi, Lin 2011), but the optimal R&D investment is unclear. Many uncertainties surround the R&D allocation problem, including the outcome of R&D (the probability of success); the value of successful R&D (impact of success on abatement cost); and the socioeconomic structure of the world.

One fundamental piece of information required for any examination of R&D policy is the expected benefit of R&D. While the effect of R&D is to improve the performance of a specific technology, the ultimate benefit of R&D is the result of the complex interactions within the economy. This research informs understanding of the value of successful R&D by examining how technological outcomes in the supply-side of the energy sector affect the cost of achieving climate targets. We use the Global Change Assessment Model (GCAM) to model a set of one thousand possible futures, each defined by a combination of expert-elicitation-derived outcomes of eight key technology parameters (Baker et al. 2015) across a range of possible socioeconomic futures based on the Shared Socioeconomic Pathways (SSP)s (O'Neill et al. 2014) under environmental constraints based on two Representative Concentration Pathways (RCP)s (van Vuuren et al. 2011). Throughout this paper, a given combination of SSP and RCP will be termed a "socioeconomic scenario".

2.1.1. The New Scenario Framework

The complex and interdisciplinary nature of the climate change problem has creates a need for a consistent framework that can support research across the socioeconomic,

[4] Unless otherwise stated, we use the term "R&D" to refer specifically to supply-side R&D.

technological, and environmental domains. Over the years, there have been several attempts to create a common set of scenarios to support climate change research. Some prominent examples include the IS92 scenarios (Leggett, Pepper & Swart 1992) and the scenarios of the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES) (Nakicenovic et al. 2000).

The passage of time, and advances in modeling and scientific understanding have created a need for updated scenarios. The so-called New Scenario Framework is designed to fulfill this need by providing *"a flexible toolkit from which researchers can create scenarios to address specific research and policy-relevant questions"* (Ebi et al. 2014). The New Scenario Framework has a three-axis architecture (Figure 1), with each axis representing a different domain of climate change research. We adapt key components of the New Scenario Framework, the Shared Socioeconomic Pathways (SSP)s and the Representative Concentration Pathways (RCP)s, to serve as the socioeconomic and environmental scenarios for this research.

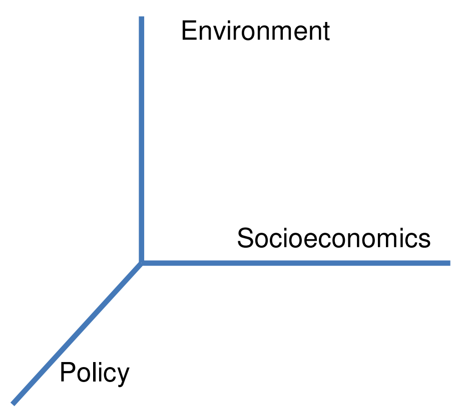


Figure 1: The scenario matrix architecture of the New Scenario Framework. Each axis represents a different domain of the climate change problem.

On the environmental axis are the RCPs, a set of detailed, internally consistent descriptions of the future (van Vuuren et al. 2011). Each RCP contains geographically gridded information on emissions of greenhouse gases and air pollutants, as well as land use. The RCPs intended to provide all of the information needed as input to climate and atmospheric chemistry models. This research uses aggregate emissions data from the RCPs as constraints to the GCAM model.

On the socioeconomic axis are the SSPs (O'Neill et al. 2014). The SSPs describe the evolution of society over the 21st century. Each SSP has a narrative storyline and an accompanying set of quantitative metrics. The SSPs are characterized by their placement within the "challenges space" (Figure 2) defined by socioeconomic challenges to mitigation and adaptation (Kriegler et al. 2014).

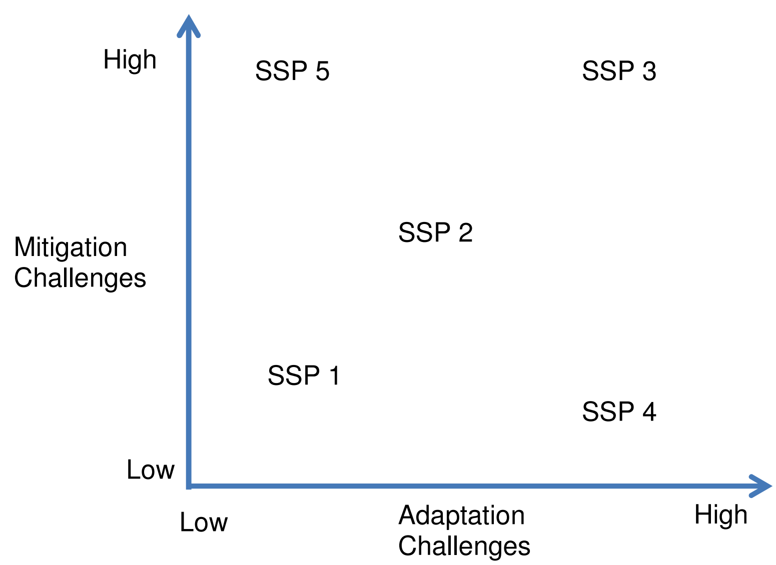


Figure 2: The Challenges space and the location of SSPs. Adapted from Kriegler et al. (2014).

Within the context of the SSPs challenges to mitigation refer specifically to factors that tend to increase emissions in the absence of climate policy, or reduce the mitigation capacity of society. This could include factors such as population, economic growth, land use, technology options, and political institutions influence reference emissions and mitigation capacity. These factors are in turn driven by more fundamental processes such as autonomous energy efficiency improvement and dietary choices. Each SSP includes specific assumptions about these drivers. It is important to note, however, that the SSPs exclude the stringency of the mitigation target and the choice of mitigation actions; by definition, these factors are accounted for by the RCP and SPA domains of the New Scenario Framework (O'Neill et al. 2014).

Challenges to adaptation are factors that increase the risks associated with any specific climate change outcome (O'Neill et al. 2014). They can arise from physical impacts such as temperature increase and sea level rise, or from socioeconomic and geographic factors such as the availability of adaptive measures, effectiveness of institutions, and the physical location (and therefore exposure) of infrastructure. The SSPs do not consider physical impacts, focusing instead on the socioeconomic aspects of adaptation.

Because the SSPs are reference scenarios and many of the other drivers discussed above are modeled explicitly in GCAM, this research adopts the population and GDP assumptions of the SSPs as inputs to the GCAM model. In what follows, reference to an “SSP” refers only to the population/GDP pathway.

A third axis contains the Shared Policy Assumptions (SPA)s (Kriegler et al. 2014). The SPAs describe three attributes of climate policy: the climate policy goals, policy regimes and measures, and implementation limits and obstacles, to the extent that these attributes are not otherwise described in either the RCPs or SSPs. The SPAs can be used to explore the impacts of policy assumptions such as fragmented participation. For simplicity, this research uses the optimal policy of global carbon price.

2.1.2. The Technology Elicitations and Modeling (TEaM) Project

Obtaining information about the effect of the potential impact of R&D is especially vexing for breakthrough technologies such as CCS or next-generation photovoltaics. While comparison to existing technologies may provide some insight (e.g. silicon wafer fabrication in the computer industry for photovoltaics (Nemet 2006)), there is often insufficient data to draw conclusions about the potential impact of R&D into as-yet-unrealized technologies.

In such circumstances, expert elicitations are often used. Expert elicitations are a structured process for obtaining information from experts (see Baker, Chon & Keisler (Baker, Chon & Keisler 2009a)) for an explanation of the elicitation process). The National Research Council of the U.S. National Academy of Sciences has recommended that the U.S. Department of Energy use expert elicitation data in its R&D funding decisions (National Research Council 2007). Expert elicitations have supported a large and growing literature, but the time and expense associated with performing elicitations has limited the number of technologies considered and methodological differences have made cross-institutional collaboration difficult.

The Technology Elicitations and Modeling (TEaM) project is a collaboration between the University of Massachusetts (UMASS), Fondazione Eni Enrico Mattei (FEEM), Harvard, the Joint Global Change Research Institute (JGCRI), and others that seeks to address these issues by aggregating a disparate selection of expert elicitations into a coherent whole. We use data from the TEaM project (Baker, Bosetti & Anadon 2015) to create a set of technology outcomes that will serve as the model inputs for our analysis.

The core of the TEaM project is three sets of expert elicitations performed at UMASS (Baker, Chon & Keisler 2009a, Baker, Chon & Keisler 2009b, Baker, Chon & Keisler 2010, Baker, Keisler 2011), Harvard (Chan et al. 2011b, Anadon et al. 2013), and FEEM (Bosetti et al. 2011b, Bosetti et al. 2011a, Bosetti et al. 2012). The elicitations consider five low carbon energy technologies: solar, nuclear, liquid biofuels, electricity from biomass, and CCS. Cost is considered for each technology, and efficiency is considered for bioelectricity, biofuels, and CCS, for a total of eight parameters. We term these eight parameters the energy technology menu (Table 1). For the balance of this paper, an unqualified reference to a "parameter" refers to one of these eight parameters.

It is important to note that while each of these parameters represents an important aspect of low carbon energy, they do not correspond to any specific project (e.g. CO2 scrubbers, catalysts, etc.). For example, the capital cost of CCS could be improved by improving any number of individual components within the CCS plant. This high-level work does not attempt to identify specific projects that may improve a parameter's performance, but rather analyzes the impact of improving that parameter's performance by whatever means.

The elicitations were harmonized after Clemen and Winkler (Clemen, Winkler 1999), and using importance sampling, TEaM developed a data set of 1000 possible future States of the World (SOW)s, each consisting of a specific value for each of the eight parameters indicated in Table 1. These samples drawn from the harmonized elicitations are termed the Elicitation Data Set (EDS). The EDS is used to generate technology scenarios that are run in GCAM. See Baker et al. (2015) for an in-depth discussion of the harmonization process and development of the EDS.

Table 1: The energy technology menu. "Short name" is the name used to refer to the parameters in the text, "elicitation units" are the units used in the expert elicitations, and "range" is the range of values considered for each parameter.

Parameter	Short Name	Elicitation Units	Range
Solar Levelized Cost of Eletricity	Solar	\$2010/kWh	0.015 – 0.447
Nuclear Overnight Capital Cost	Nuclear	\$2010/kW	242 – 10,500
Bioliquids Non Energy Cost	Bioliquids Cost	\$2010/GGE	0.22 – 10.55
Bioliquids Efficiency	Bioliquids Efficiency	% HHV	19.0 – 85.0
Bioelectricity Non Energy Cost	Bioelectricity Cost	\$2010/kWh	0.006 – 0.232
Bioelectricity Efficiency	Bioelectricity Efficiency	% HHV	6.0 – 85.0
CCS Additional Capital Cost	CCS Cost	\$2010/kW	1.55 – 3920
CCS Energy Penalty	CCS Efficiency	%	2.0 – 43.0

2.1.3. GCAM

A significant challenge of this research is characterizing the effect of specific performance parameters of individual energy technologies on the ultimate cost of achieving environmental targets. We choose GCAM for this task because as a technology-rich integrated assessment model, GCAM contains detailed representations of technology options in all sectors of the economy (McJeon et al. 2011). This detailed representation allows us to independently manipulate individual parameters within a technology.

GCAM is a global integrated assessment model of climate, economy, energy, and land-use, developed and maintained by the Joint Global Change Research Institute. GCAM is built on the foundations of MiniCAM (Edmonds et al. 2004, Kim et al. 2006), which, in turn, was a descendant of a model developed by Edmonds & Reilly (1985). The full documentation of the model is available at the GCAM wiki (Joint Global Change Research Institute 2012); here we highlight those aspects of the model most important to this research.

Market competition drives energy technology choice in GCAM. A logit-based probabilistic model determines the market shares of each technology based on the relative prices of technologies (Clarke, Edmonds 1993, McFadden 1974). Market prices for technologies are based on the technological characteristics of each technology, as well as market factors such as the cost of inputs and the price of outputs. This methodology assumes that heterogeneous suppliers and purchasers exist in every market. Each actor may have different needs and the local price they experience may be different across geographic regions. Therefore, a single dominant technology may not necessarily take over the market in all conditions, even if the average price of the technology is lower than the other options. This formulation ensures that relatively higher-priced goods gain some market share, consistent with real market observations of heterogeneous behavior.

Agriculture and land use are modeled in GCAM via the Agriculture and Land Use (AgLU) model. AgLU competitively allocates land area among possible land uses, and tracks both production and carbon flows due to land use. Competition among land uses is modeled with a logit model similar to the one used in the energy system; land is allocated among possible uses according to its expected profitability, which is contingent upon the profitability of the underlying agricultural product (Wise, Calvin 2011).

Land use plays an important role in climate change. Conversion of grassland to agricultural uses results in net CO2 emissions, while terrestrial carbon reservoirs such as forests offer a means of capturing atmospheric carbon. Additionally, GCAM's representation of bioenergy allows bioelectricity to be combined with CCS, creating the possibility that carbon sequestered from the atmosphere in the production of biomass feedstocks could be captured and permanently removed from the atmosphere, resulting in energy production with negative CO2 emissions (Wise, Calvin 2011). These land use characteristics can have important implications for the energy system, especially for biomass energy technologies.

Energy form biomass is linked to both the energy and AgLU modules of GCAM. Demand for biomass feedstocks is determined by the energy module, while their supply characteristics are derived from AgLU. In the energy module, biomass competes alongside other energy options; as the price of carbon increases biomass energy becomes more valuable and therefore able to support higher prices for biomass feedstocks. In the AgLU module increased demand for biomass feedstocks would place competitive pressure on other land uses, potentially resulting, for example, in higher crop prices. Conversely, population and GDP factors affect demand for agricultural products, and carbon pricing may encourage conservation or expansion of terrestrial carbon reservoirs such as forests.

GCAM models a variety of biomass resources. Four prominent categories are traditional biomass, residual biomass, biomass from food crops, and purpose-grown bioenergy crops. Traditional bioenergy is derived from unrefined biomass feedstocks consumed in the traditional sector of the economy. Residual biomass is a byproduct of other economic activities (e.g. crop residues), and its availability is determined by the production of the underlying non-energy product. Biomass from food crops represents crops currently in wide production today that are grown for energy, rather than food, and purpose grown biomass are crops such as switchgrass and jatropha whose primary purpose is energy production.

The economic simulation of GCAM is driven by exogenous assumptions about population size and GDP. GCAM is solved in 5-year time steps through 2095 by establishing market-clearing prices for all energy, agriculture, and land markets; 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.

Specific targets for atmospheric CO_2 concentration are implemented by exogenous emissions trajectories. The cost of climate stabilization is calculated by the integration of the area under the marginal abatement cost curve for each period. The discounted sum of annual stabilization cost from 2005-2095 yields net present value of the total cost of stabilization, which we term the “cost of abatement”. For discounting future values, a real discount rate of 5% per year is used.

2.2. Methods

2.2.1. Adapting the New Scenario Framework to GCAM

The International Institute for Applied Systems Analysis (IIASA) maintains a database of the quantitative projections of the SSP parameters (International Institute for Applied Systems Analysis 2013). As discussed in 1.3, population and GDP are exogenous in GCAM. The population and GDP projections of the database were used as the basis for the population and GDP specifications for the model runs.

SSPs 1-3 were chosen for this analysis. SSP1 represents a scenario with low challenges to mitigation and adaptation: population peaks at about 8.5 billion in the mid-21st century before declining, and GDP grows strongly, leading to a global per-capita GDP of approximately 45,000 2010 USD in 2100. In contrast SSP3 represents a world with high challenges to adaptation and mitigation, with population rising to 12.5 billion by 2100, and per capita GDP rising slowly to about 12,500 2010 USD by the end of the century. SSP2 is a scenario between these two extremes, with population peaking near 9.5 billion in 2070 and GDP per capita of ~31,000 2010 USD. The population, GDP and per-capita income pathways of SSPs 1-3 are shown in

Figure 3,

Figure 4, and

Figure 5.

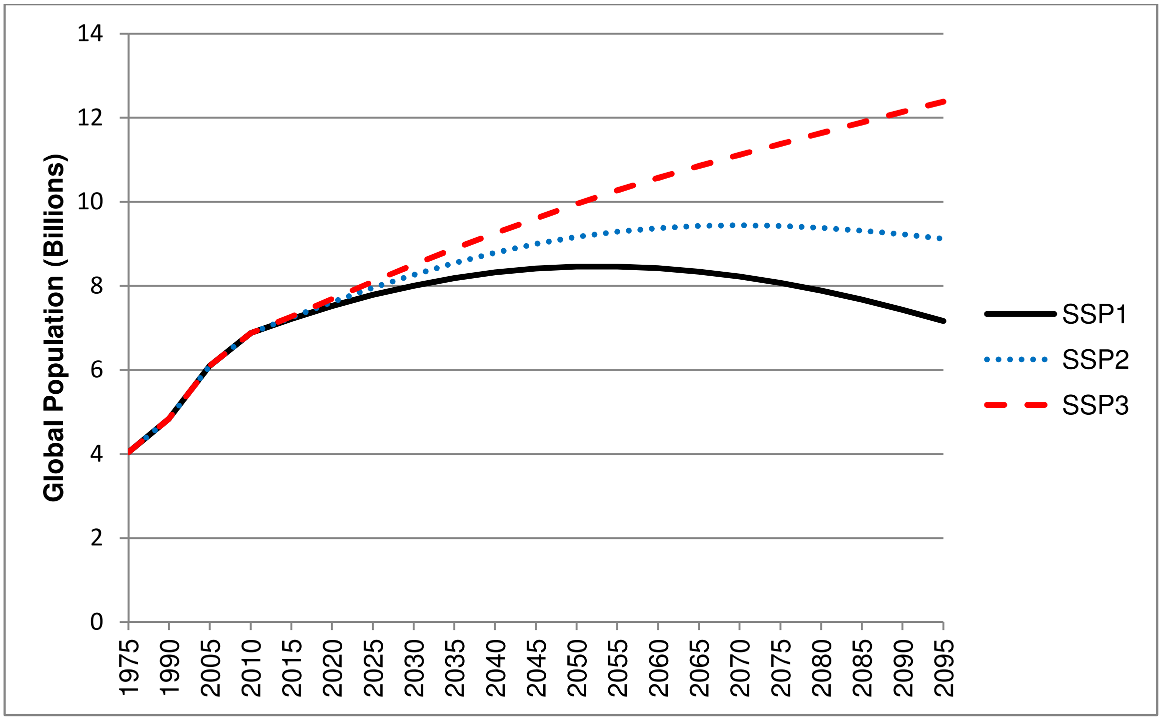


Figure 3: Population pathways for SSPs 1-3.

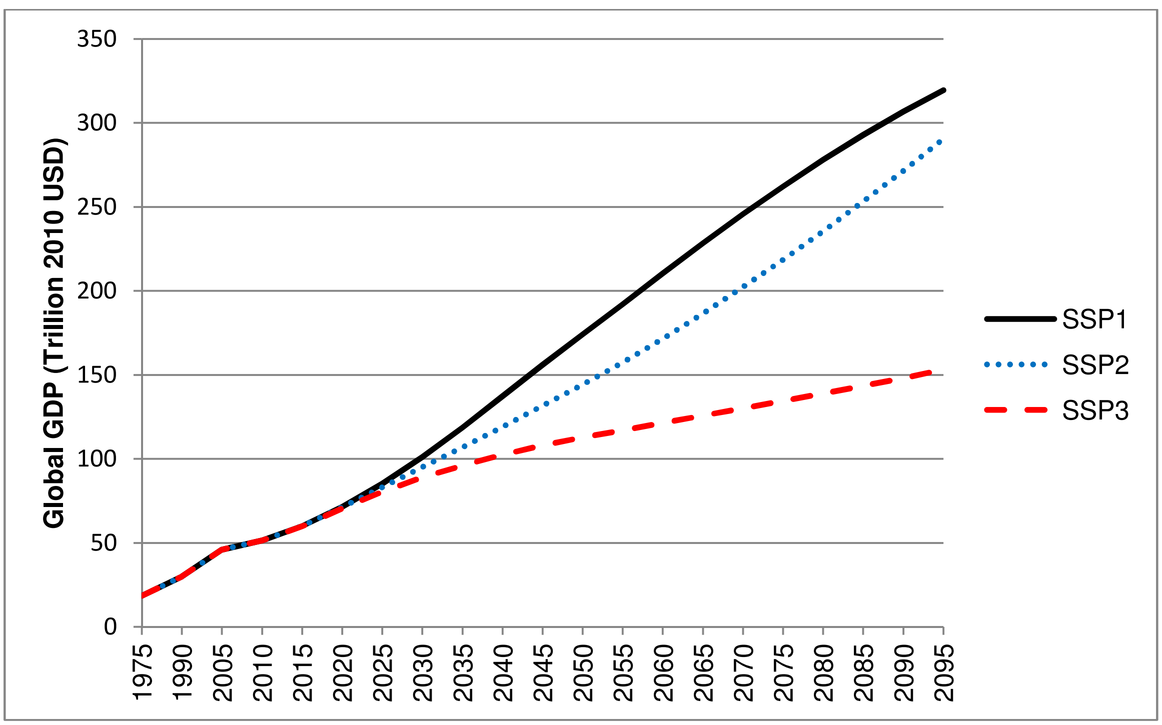


Figure 4: GDP pathways for SSPs 1-3.

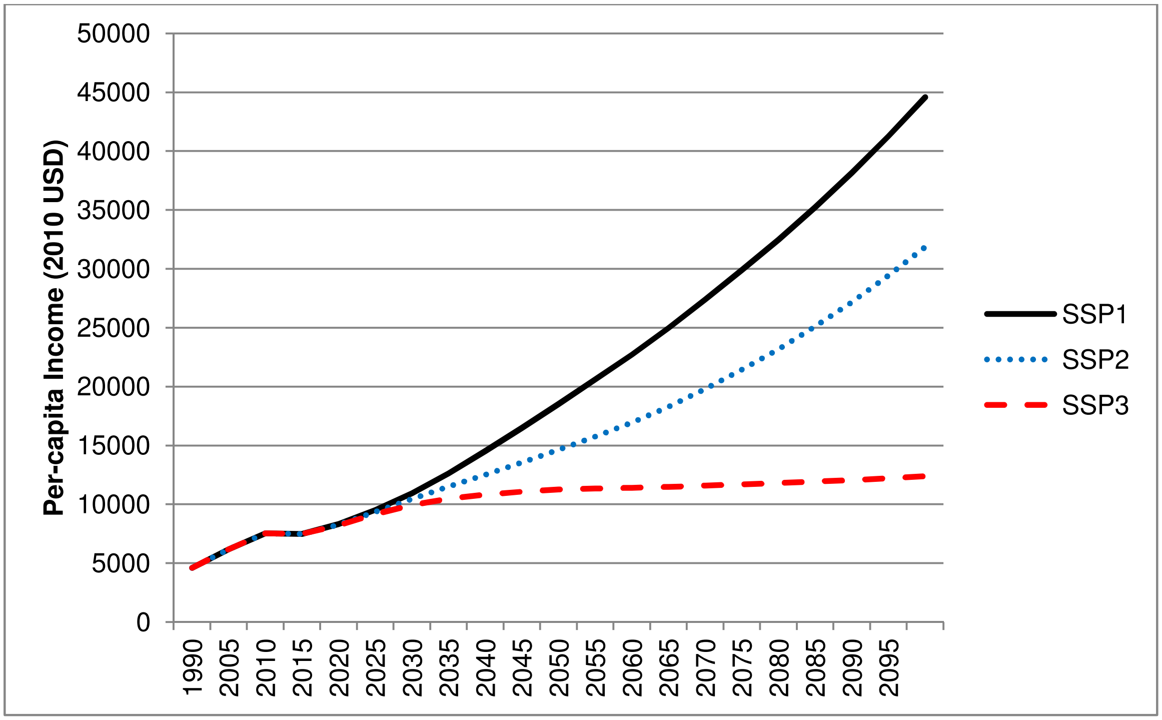


Figure 5: Per-capita GDP for SSPs 1-3.

In a similar manner, the CO2 emissions constraints for our model runs are based on the RCP 2.6 and RCP 4.5 concentration pathways. These constraints were implemented in GCAM by applying the respective RCP fossil fuel CO2 emissions as a constraint on CO2 emissions.

2.2.2. Generating Technology Inputs

As discussed in section 2.1.2, the EDS consists of one thousand different possible SOWs. Each SOW corresponds to a particular value in 2030 for each of the eight technology parameters in the energy technology menu. These static values were converted into GCAM inputs in a two-step process: the elicited values were first converted into GCAM compatible units and then parameterized into performance curves that span the entire time horizon of the model.

Two of the parameters, solar and bioelectricity cost, required only trivial unit conversions. Bioliquids cost, bioliquids efficiency, and bioelectricity efficiency required assumptions about the Lower Heating Values (LHV), Higher Heating Values (HHV), and the energy content of a Gallon of Gasoline Equivalent (GGE). Here we used values published by the Oak Ridge National Laboratory (Boundy et al. 2011). The remaining parameters, CCS cost, CCS energy penalty, and Nuclear, required more complex calculations involving capital recovery factor, plant lifetime, capacity factor, CCS capture rate, and thermal efficiency; these calculations used GCAM 2.1 default assumptions whenever applicable.

Once converted into GCAM compatible units the values from the EDS were parameterized as follows. Let $\boldsymbol{X}$ be the Elicitataion Data Set (EDS). Let $i = \{1, 2, \dots, 1000\}$ index the samples and $j = \{1, 2, \dots 8\}$ index the technology parameters and. Let $x_{i,j}$ be an individual element of the EDS, $\boldsymbol{x}_j = \{x_{1,j}, x_{2,j}, \dots x_{1000,j}\}$ be the set of parameter values for parameter j, and $\boldsymbol{x}_i = \{x_{i,1}, x_{i,2}, \dots x_{i,8}\}$ be a vector of all eight parameters for a single State Of the World. The parameter values x_{ij} are parameterized into cost curves according to the following formula:

$$x_{ij}(t) = x_{ij}(2005) + \frac{x_{ij}(2030) - x_{ij}(2005)}{1 - \beta}\left(1 - \beta^{\frac{t-2005}{2030-2005}}\right) \quad \textbf{(1)}$$

s.t

$$\min[\boldsymbol{x}_j] \leq x_{ij}(t) \leq \max\,[\boldsymbol{x}_j]$$

$$x_{ij}(t) \geq \frac{x_{ij}(t)}{2}$$

where $x_{ij}(t)$ is the parameter value at time t, β determines the proportion of the change in $x_{ij}(t)$ occurring after 2030, and $\min[\boldsymbol{x}_j]$ and $\max[\boldsymbol{x}_j]$ are the minimum and maximum parameter values for technology j, respectively. The initial value $x_{ij}(2005)$ is taken from the GCAM default assumption and $x_{ij}(2030)$ is the parameter value given by the elicitation data set. Although parameter values generally improve, parameters are allowed to grow worse through time. This reflects possible unforeseen circumstances such as scarcity, unknown technological "surprises" that require additional costly efforts in the future, or exogenous cost impacts such as environmental regulations.

2.2.3. The Critical Performance Level and Magnitude of Impact

The basis for the analysis are hypothesis tests that compare the mean policy cost of "test blocks" of progressively higher performance parameter values against a "base" block composed of the worst parameter values, for each individual parameter (Figure 6). Successively higher performance test blocks are compared until the mean policy cost of the test blocks is consistently significantly different ($\alpha < 0.05$) from the base block. The point at which this occurs is termed the Critical Performance Level (CPL). If a CPL exists, the magnitude of the impact is characterized by the percentage difference between the mean policy cost of the scenarios above and below the CPL.

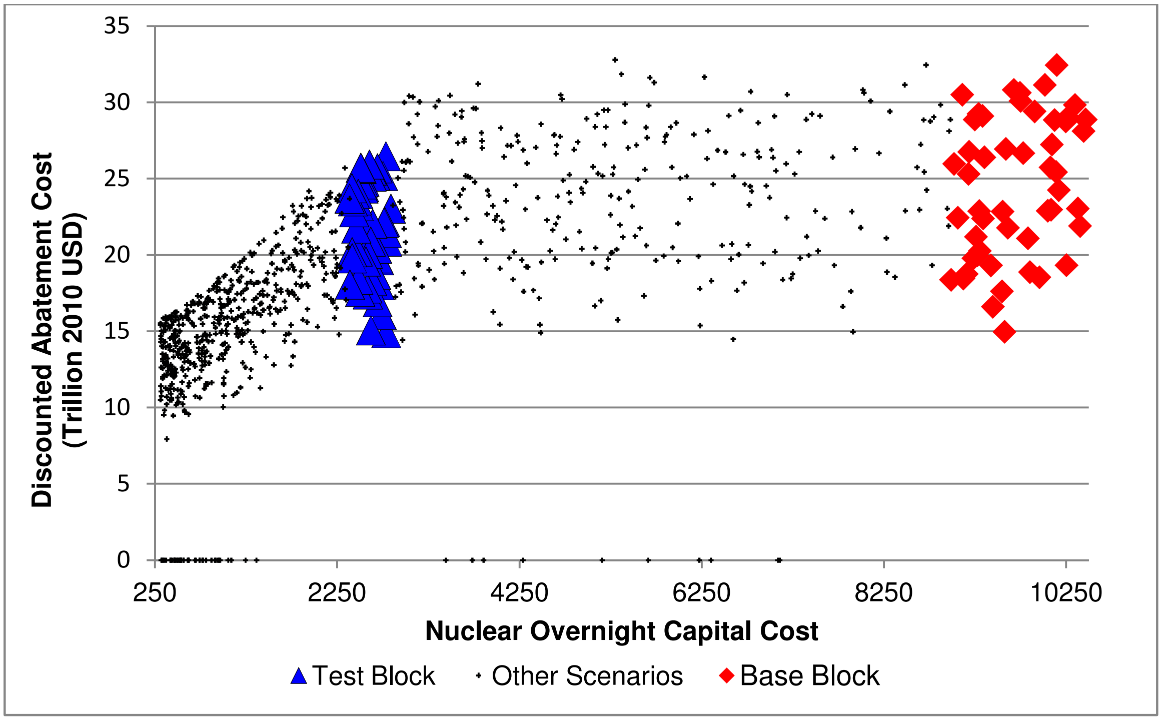


Figure 6: Illustration of significance testing methodology. The base block (diamonds) is composed of the fifty worst-performing points in the EDS. A test block (triangles) is composed of fifty adjacent data points in the EDS. The CPL is determined by iteratively performing t-tests between all possible test blocks in order of improving performance and determining the point at which the test blocks are consistently significantly different ($\alpha = 0.05$) from the test block. Points on the x-axis indicate missing data and are treated as such in the hypothesis tests.

To formalize the process described above, let $\mathrm{U_j} = \left\{(\mathrm{x_{ij}})_1, (\mathrm{x_{ij}})_2, \dots (\mathrm{x_{ij}})_n\right\};\ (\mathrm{x_{ij}})_1 < (\mathrm{x_{ij}})_2 < \cdots < (\mathrm{x_{ij}})_{n-1} < (\mathrm{x_{ij}})_n$ be the set of parameter values for technology j arranged in order from lowest to highest performance. Let $\mathrm{k} = \{1, 2, \dots \mathrm{n}\}$ index the elements of U_j, so $\mathrm{u_{j,k}} \in \mathrm{U_j}$ represents $(\mathrm{x_{ij}})_k$, the k^{th} best performing parameter value in $\mathbf{x}_\mathrm{j}$. Similarly, define $Y_j = \left\{(y_j)_1, (y_j)_2, \dots (y_j)_n\right\}$ as the set of corresponding GCAM outputs, so $(y_j)_k$ is the GCAM output corresponding to input $\boldsymbol{x}_i$.

Now, define a test block $\hat{y}_{j,k} = \{y_{j,k-49}, y_{j,k-48}, \dots, y_{j,k}\}$ as a subset of Y_j composed of fifty adjacent elements of the set and $\bar{y}_{j,k}$ as the mean value of the elements of $\hat{y}_{j,k}$.

Define the base block $\hat{y}_{j,base} = \hat{y}_{j,n}$ as the test block composed of the outcomes corresponding to the fifty worst parameter values in U_j.

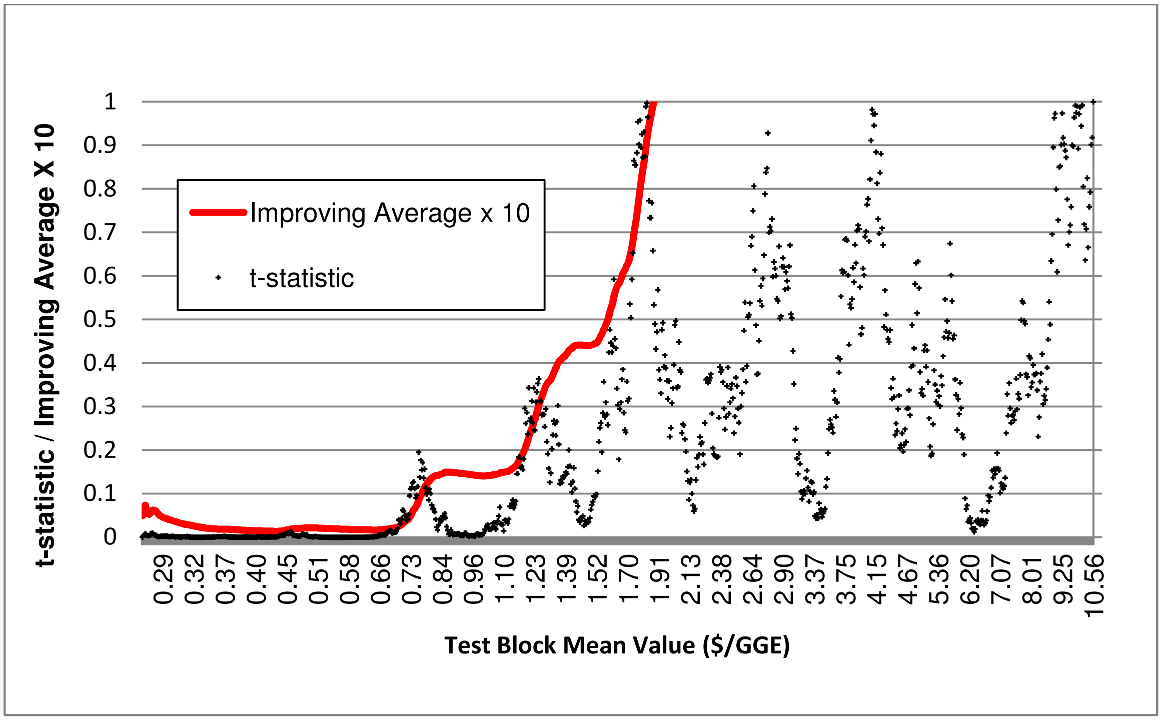
Let $\alpha_{j,k}$ be the Student's t-statistic corresponding to the Student's t-test between $\hat{y}_{j,base}$ and $\hat{y}_{j,k}$. Let $\bar{\alpha}^{+}_{j,k} = mean\{\alpha_{j,k}, \alpha_{j,k+1}, \dots, \alpha_{j,n}\}$ be the mean value of all the t-statistics of the test blocks composed of elements at least as well-performing as $u_{j,k}$. In what follows $\bar{\alpha}^{+}_{j,k}$ will be referred to as the "improving average".

The CPL $\bar{x}^{*}_{j,k}$ is defined as the mean of the parameter values corresponding to the test block $\hat{y}^{*}_{j,k}$, the worst performing test block for which all $\bar{\alpha}^{+}_{j,k}, \bar{\alpha}^{+}_{j,k+1}, \dots, \bar{\alpha}^{+}_{j,n}$ are below 0.05.

A parameter's impact Δ_j on abatement cost is calculated as the percent difference in abatement cost between the mean value of the abatement cost of scenarios above and below the critical value:

$$\Delta_j = \frac{\bar{y}^{+}_{j,crit} - \bar{y}^{-}_{j,crit}}{\bar{y}^{+}_{j,crit}} \tag{2}$$

Figure 7 illustrates the relationship between $\alpha_{j,k}$, $\bar{\alpha}^{+}_{j,k}$, and the CPL. The upper panel plots data for bioliquids cost, which has a CPL, and the lower panel plots data for bioliquids conversion efficiency, which does not. Both plots are for results under SSP 2 and RCP 2.6. Note that in cases where a CPL exists, as in the upper panel, a clear change in the pattern of the values is observed, which is reflected in $\bar{\alpha}^{+}_{j,k}$. A similar pattern is absent when a CPL does not exist, as in the lower panel.



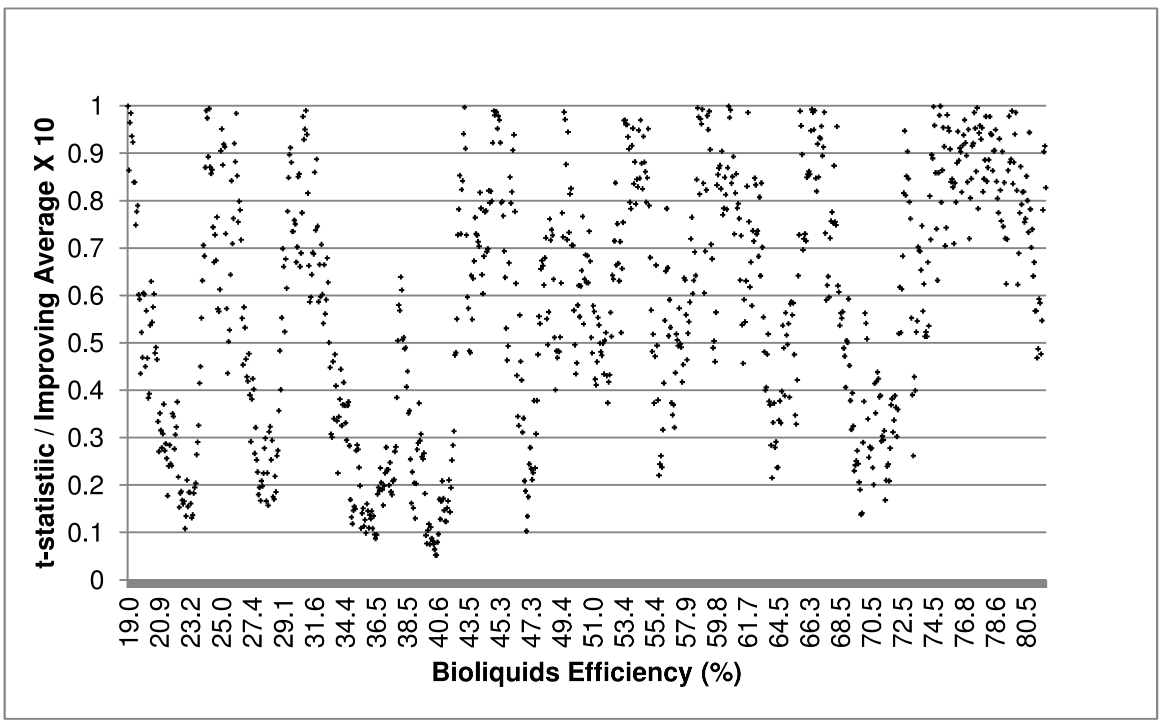


Figure 7: Illustration of the relationship between t-statistics, improving average, and CPL. Upper panel: Bioliquids cost under SSP2 and RCP 2.6 has a CPL of $1.47 / GGE. This figure overlays plots of the t-statistic $\alpha_{j,k}$ and imporving average $\overline{\alpha}_k^+$ versus the test block mean parameter value $\overline{y}_{j,k}$. Note that $\overline{\alpha}_k^+$ is scaled for clarity. The critical value is the point at which $\overline{\alpha}_k^+$ drops below 0.05 (0.50 on the figure). Lower panel: Bioliquids efficiency under SSP2 and RCP6 has no CPL.

2.3. Results

2.3.1. Analysis of Model Runs

Each of the parameters was analyzed as described in Section 2.2.3. Table 2 summarizes the critical values of the parameters across the socioeconomic scenarios. Two parameters, bioliquids efficiency and CCS energy penalty, never have a CPL – that is, there was no evidence of these parameters having an impact on abatement cost across the range of parameter values studied for any of the socioeconomic or climate policy scenarios. Of the remaining parameters, solar and bioelectricity efficiency did not have critical values in at least one scenario, and generally had critical values near the high performance end of the test range. Nuclear, bioliquids and bioelectricity cost, and CCS cost all have critical values across all socioeconomic scenarios considered. Nuclear shows a consistent CPL of around $4500/kW. The CPL for CCS cost is increasing in the stringency of the carbon constraint and is approximately 50% lower in SSP3 than in the other SSP scenarios. In contrast, bioliquids cost has a higher CPL in SSP3 than in the other SSP scenarios. Just as with bioliquids cost, the CPL of bioelectricity cost is generally increasing in the stringency of the carbon constraint, except in SSP3, where the CPL is nearly the same under both RCP constraints.

Table 2: Critical Performance Levels for parameters.

		Solar LCOE	Nuclear Overnight Capital Cost	Bioliquids Non-Energy Cost	Bioliquids Conversion Efficiency	Bioelectricity Non-Energy Cost	Bioelectricity Conversion Efficiency	CCS Additional Capital Cost	CCS Energy Penalty
RCP 2.6	SSP1	$0.175	$4,613	$3.96	-	$0.107	33.0%	$2,981	-
	SSP2	$0.017	$4,550	$1.47	-	$0.100	75.1%	$2,881	-
	SSP3	-	$4,676	$5.01	-	$0.101	74.6%	$1,529	-
RCP 4.5	SSP1	$0.019	$4,651	$1.09	-	$0.047	-	$1,156	-
	SSP2	$0.019	$4,658	$1.42	-	$0.058	75.0%	$1,229	-
	SSP3	$0.019	$4,486	$9.47	-	$0.100	67.0%	$545	-

Table 3: Impact of parameters on abatement cost.

		Solar LCOE	Nuclear Overnight Capital Cost	Bioliquids Non-Energy Cost	Bioliquids Conversion Efficiency	Bioelectricity Non-Energy Cost	Bioelectricity Conversion Efficiency	CCS Additional Capital Cost	CCS Energy Penalty
RCP 2.6	SSP1	10%	22%	6%	-	11%	11%	7%	-
	SSP2	-	27%	11%	-	13%	9%	9%	-
	SSP3	-	26%	9%	-	15%	10%	6%	-
RCP 4.5	SSP1	-1%	31%	11%	-	10%	-	10%	-
	SSP2	7%	36%	12%	-	13%	14%	7%	-
	SSP3	7%	37%	22%	-	18%	14%	8%	-

As discussed in section 2.2.3 the magnitude of the impact of those technology parameters that have a CPL is characterized by their effect on the cost of abatement; Table 3 summarizes these cost impacts. Nuclear shows the strongest impact in all cases, with impacts ranging from 22-37%. Bioelectricity cost has a consistent impact across scenarios of around 10-15%. Bioelectricity's impact is second only to nuclear under RCP 2.6. However, under RCP 4.5 bioelectricity and bioliquids cost have similar impacts of around 10%, except for SSP3, where the impact of both parameters is around 20%. Bioelectricity efficiency generally has about equal or slightly less impact than bioelectricity cost, however the CPL of bioelectricity efficiency is high (about 75%) in SSP2 and SSP3. Bioliquids cost and CCS cost have similar impacts in the range of 6-12% except under RCP 4.5 and SSP3, where bioliquids cost an impact of 22%, second only to nuclear. Solar has diverse impacts, ranging from none in two of six cases, to a maximum of about 10%, but has a CPL at the extreme high-performance end of the test range (< \$0.02/kWh) an all but one case, SSP1 under RCP 2.6.

2.3.2. Missing Data

An important characteristic of the EDS is that the set of values for each parameter is generated by sampling from a probability distribution, meaning that each SOW is a collection of realizations of random variables. As such, a particular state of the world is not necessarily plausible, likely, or technologically consistent, which can lead to solvability issues when such a SOW is modeled in GCAM. When GCAM is unable to solve we treat that particular SOW as missing data.

Our approach to missing data is the method of listwise deletion. Listwise deletion discards incomplete records without attempting to account for their effect. Listwise deletion has the merit of simplicity; however, because incomplete records are simply discarded, the statistical power of the hypothesis tests are reduced and bias may be introduced if there is a pattern to the missing data (e.g. if the data is not missing at random).

Missing data always reduces the power of a hypothesis test; in other words, the probability of a Type II error is increased. In terms of our methodology increasing the probability of Type II error will tend to increase the value of the improving average $\bar{\alpha}_{j,k}^{+}$, which will in turn bias the CPL towards higher performance.

If the missing data is not Missing At Random (MAR), $\bar{y}_{j,k}$ will also be biased, which will affect the magnitude of the effect Δ_j. The effect of non-MAR data on Δ_j depend on the direction of the bias. Under the assumption that if an CPL exists abatement cost is monotonically decreasing in improving performance of a parameter, missing data biased toward higher performance parameter values will bias the mean discounted abatement cost of the affected test blocks higher, which will in turn reduce Δ_j. Conversely, missing data biased toward lower performance parameter values will increase Δ_j.

In order to determine if the data was MAR, a t-test was performed between the parameter values of the missing data points and the full data set. A finding of significance ($\alpha < 0.05$) indicates that the two samples were drawn from different distributions, which we interpret as meaning that the data is not Missing at Random (MAR). Absent a finding of significance, we make the assumption that the data is MAR. In cases where the data is MAR we assume that the associated (test and/or base) block means are unbiased and the missing data affects only the CPL If the data is not MAR, we assume the block means will be biased and we will also need to consider the effect of the bias when interpreting the results.

Table 4 summarizes the characteristics of the missing data. The top two lines show the number and percentage of missing points. The rows below show the t-statistic for the comparison between the missing data points and the entire EDS. Boldface indicates a finding of significance. Nuclear always shows a significant relationship to missing data, and bioliquids cost nearly always so. The only parameter that never has a significant relationship to the missing data is the CCS Energy penalty.

Table 4: Summary of missing data. Bold indicates a significant difference ($\alpha < 0.05$) between the missing data and the entire set, in these cases we assume the data is not missing at random.

	SSP1		SSP2		SSP3	
	RCP 2.6	RCP 4.5	RCP 2.6	RCP 4.5	RCP 2.6	RCP 4.5
Number Missing	271	159	64	32	46	53
Percent Missing	27.1%	15.9%	6.4%	3.2%	4.6%	5.3%
Solar	**0.0023**	0.2916	0.0554	**0.0000**	**0.0000**	**0.0005**
Nuclear	**0.0000**	**0.0000**	**0.0003**	**0.0023**	**0.0004**	**0.0000**
Bioliquids Cost	0.0839	0.9534	**0.0059**	0.7618	0.1177	0.9900
Bioliquids Efficiency	0.4635	**0.0000**	0.5723	0.9107	0.0631	0.4648
Bioelectricity Cost	0.1727	**0.0025**	0.7200	**0.0183**	0.7468	0.1068
Bioelectricity Efficiency	0.9620	**0.0000**	0.6473	**0.0000**	0.1087	**0.0091**
CCS Cost	0.5933	**0.0000**	0.0635	**0.0307**	0.1019	**0.0170**
CCS Energy Penalty	0.4781	0.6377	0.2232	0.4678	0.9838	0.1640

Table 5 details the percent difference between the mean parameter values of the missing data and the entire EDS. In cases where there is statistically significant difference between the missing data and the complete EDS, test blocks containing missing data will be biased. Positive percentages indicate that the parameter values associated with missing data are biased toward higher parameter values, negative percentages indicate that the parameter values are biased toward lower parameter values. We discuss the implications of the missing data in Section 2.4.

Table 5: Percent difference between mean abatement cost of missing data and complete EDS. Boldface entries indicate scenarios where missing data is assumed to be not MAR.

	SSP1 RCP 2.6	RCP 4.5	SSP2 RCP 2.6	RCP 4.5	SSP3 RCP 2.6	RCP 4.5
Number Missing	271	159	64	32	46	53
Solar	**19%**	-7%	22%	**47%**	**-56%**	**-46%**
Nuclear	**68**%	**70%**	**46%**	**49%**	**52%**	**-53%**
Bioliquids Cost	12%	7%	**37%**	13%	24%	8%
Bioliquids Efficiency	2%	**1%**	3%	13%	10%	11%
Bioelectricity Cost	-9%	**-24%**	-4%	**-38%**	5%	13%
Bioelectricity Efficiency	0%	**10%**	-3%	**18%**	-12%	**0%**
CCS Cost	2%	**4%**	14%	**6%**	14%	**3%**
CCS Energy Penalty	3%	4%	9%	10%	0%	3%

2.4. Discussion

These results illustrate several important points. Perhaps the most obvious is the importance of nuclear energy. Nuclear has the strongest impact on abatement costs across all of the socioeconomic and climate policy scenarios considered. Nuclear's impact is double edged: not only does inexpensive nuclear reduce the cost of abatement, expensive nuclear raises minimum abatement costs. This can be seen in Figure 8, which compares the two most impactful parameters under SSP 2 and RCP 2.6, nuclear and bioelectricity cost. At high costs nuclear shows a minimum abatement cost of around 15 trillion dollars, while the minimum abatement cost under high bioelectricity cost is around 10 trillion dollars. Similar patterns are present in nuclear's impact across all scenarios considered. Conversely, low nuclear prices lower the maximum abatement cost, while lower bioelectricity prices do not.

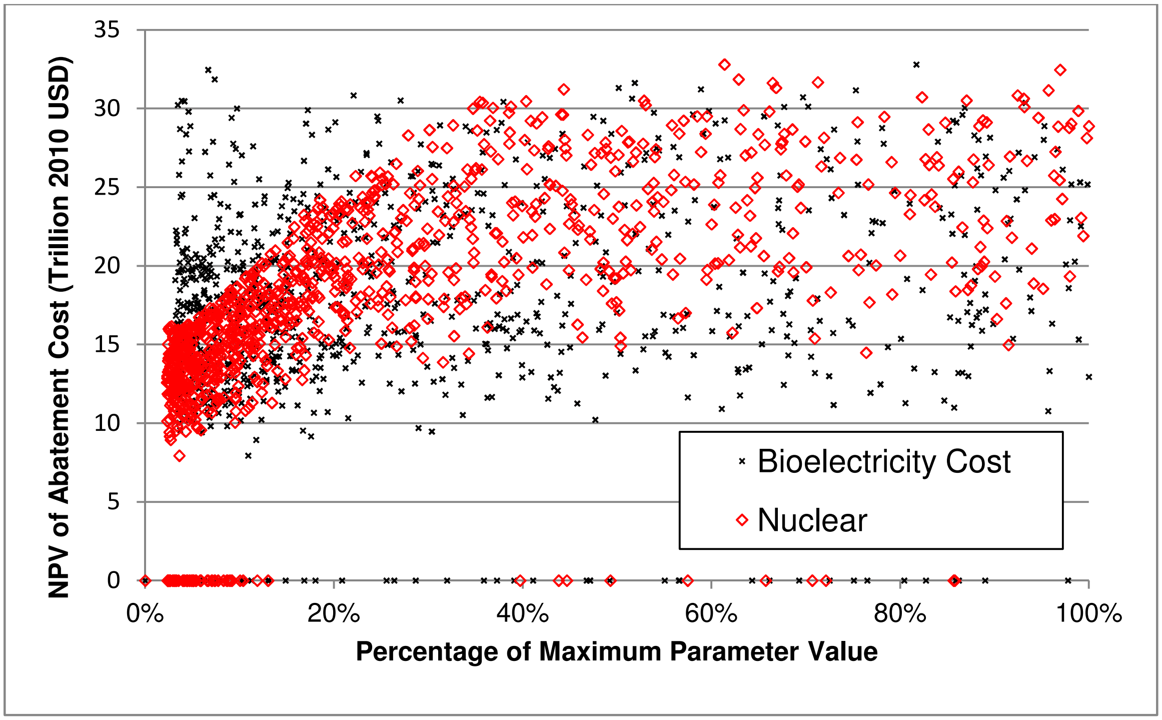


Figure 8: Comparison of nuclear and bioelectricity cost under RCP 2.6 and SSP2. Nuclear shows higher minimum abatement cost at high prices, and lower maximum cost at low prices, compared to bioelectricity cost. Points on the x-axis indicate missing data.

Biomass technologies play an important role. The lack of significance for bioliquids efficiency and relatively high critical values for bioelectricity efficiency, however, implies that trading efficiency for lower cost may be worthwhile strategy for improving the value of biomass. Biomass technologies may also provide a form of "hedging" against less wealthy socioeconomic outcomes; both bioelectricity cost and bioliquids cost have lower performance CPLs under SSP3 than in other scenarios.

Like the biomass technologies, the cost of CCS technology is significant while the energy penalty is not. Here again an inexpensive technology may be preferred to an efficient one. However, unlike biomass, CCS becomes less valuable under SSP3, indicating that the value of CCS technology is sensitive to socioeconomic development.

These results also indicate that cost reduction in solar cells alone may be unlikely to substantially reduce abatement cost. While the cost of solar was found to be significant in most scenarios, the CPL of solar was extremely low (< $0.02/kWh) in all but one case. This may be a consequence of solar's non-dispatchability. Solar, like other non-dispatchable technologies, must pay a penalty that reflects the costs that non-dispatchable generation impose on the grid. In GCAM these so-called (grid) integration costs are modeled by requiring non-dispatchable generation to be combined with either backup or storage, at an additional cost, according to a ratio governed by market share. At low market share little backup/storage is required but at higher market share each additional unit of non-dispatchable generation requires an additional unit of storage. Consequently, if the market share of non-dispatchable generation is high the total cost of solar energy may be high even if the capital cost of the solar panels themselves is low. This result is consistent with Baker, Chon & Keisler (2009a), who concluded that even large advances in solar technology had a small impact on abatement costs unless paired with improved storage technology.

Solar's performance could also be affected by our exogenous assumption that a parameter's post 2030 value cannot be less than half of its 2030 value. This is because the total change in a parameter's value is proportional to the difference between its initial (2005) value and its elicited (2030) value. Relative to the other parameters considered, solar's initial value is much higher than its elicited values and therefore more likely to be affected by this constraint. In about half of the cases in this analysis solar's price was constrained by this assumption, more than any other technology.

Socioeconomics play an important role in the outcomes, particularly with respect to SSP3, the most populous and least wealthy scenario. The impact of bioliquids cost, and the CPLs of bioelectricity and CCS cost all show substantial differences under SSP3. This is especially true under RCP 4.5, where the CPL and impact of bioliquids cost both improve while the corresponding values for CCS cost get worse. SSP3 represents a world with high challenges to both adaptation and mitigation, with the highest population and lowest GDP of the socioeconomic scenarios considered in this work. These differences suggest that careful attention should be paid to the underlying socioeconomic assumptions, both in future research and in policy decisions, especially since a policy “mistake” could be relatively more costly in the relatively less wealthy world of SSP3.

The stringency of the climate stabilization constraint also affects outcomes, particularly for CCS and bioelectricity cost. Compared to the results under RCP 2.6., under RCP 4.5 the CPL of CCS is reduced by approximately 60% across all SSP scenarios considered. Similarly, under RCP 4.5 the CPL of bioelectricity cost is reduced by about half in SSP1 and SSP2, and about 10% in SSP3 compared to RCP 2.6. On the other hand, nuclear’s CPL changes by less than 5% across the SSP scenarios considered.

It is important to note that the impact of a parameter is conditional on achieving the critical value. Therefore, in addition to the magnitude of a parameter’s impact the level at which a parameter becomes significant is also important. For example, while the results indicate that solar energy has a significant effect under five of the six scenarios, the critical value is below \$0.02 /kWh, so the probability of solar achieving its critical value may be very low. Bioliquids cost also has very high performance CPLs of < \$1.50/GGE in several scenarios, although its much lower-performance CPL in SSP3 may give it value as a "hedge" against high population/low GDP scenarios. As discussed in Section 2.2.2 the process of converting the EDS to GCAM inputs required a number of economic and technological assumptions (e.g. capital recovery factor, plant lifetime). For consistency these assumptions follow GCAM's defaults whenever possible. While these assumptions affect the specific values of the elements of $\boldsymbol{x}_j$ they are not likely in and of themselves to change the overall insights about the existence of a CPL or the magnitude of a parameter's impact.

Finally, the effect of the missing data must be considered. In all cases where there is missing data the probability of a Type II error will be increased, which will in turn increase the value of $\bar{\alpha}^{+}_{j,k}$. The implication for these results is that missing data will bias the CPL toward higher performance.

In those cases where the assumption of MAR fails, (bold entries in Table 4) the estimate of mean discounted abatement cost ($\bar{y}_{j,k}$) will be biased for those test blocks with missing data. Nuclear's missing data has a strong bias toward higher performance parameter values. The same is true for bioelectricity cost in those cases where our assumption of MAR fails. For both parameters, the bias of the missing data toward higher performance will tend to reduce the value of Δ_j, meaning that our calculated effect is biased toward a smaller effect. On the other hand, the missing data for bioelectricity efficiency and CCS cost have biases toward higher parameter values when our MAR assumption fails. In the case of bioelectricity efficiency, where higher values indicate higher performance, this will bias the results toward a smaller effect, and in the case of CCS cost, toward a larger one. The net effect will be to make nuclear, bioelectricity cost, and bioelectricity efficiency look less attractive while making CCS cost look more attractive. Taken together, these biases generally make the most impactful technologies look less so, and the least impactful technologies more so. The one exception to this pattern is solar, where the bias can be in either direction, depending on the scenario.

When looking at the impact of missing data on the results as a whole, the missing data tends to shift CPLs toward higher performance and reduce the magnitude of impact (if any) for individual parameters; these effects are consequences of our methodology and would be present regardless of the parameters considered. With respect to the specific parameters considered here, missing data narrows the performance gap, so our qualitative observations about the relative values of the technology parameters would not change if bias was removed, although the quantitative measures of the performance metrics would change.

2.5. Conclusions & Policy Implications

So what insights can be gleaned from these results? The strongest message is that controlling the cost of nuclear technology is critical to controlling the cost of climate stabilization. Among the technologies considered, nuclear technology shows the largest and most consistent impact on abatement costs. Low cost nuclear has significant benefits and expensive nuclear raises the minimum total cost of abatement. This underscores the importance of capital cost reduction in nuclear reactors in minimizing abatement cost. This could partly be accomplished by R&D in nuclear technologies, but is also affected by other exogenous factors, such as commodity prices and labor costs. In any event, policies supporting nuclear technology appear to be vital to controlling abatement costs.

Another important insight is the relative value of biomass and CCS technologies. Biomass technologies generally have larger impacts than CCS and are less sensitive to the climate stabilization scenario, particularly under SSP3. This argues for prioritizing biomass technologies over CCS, especially in the face of uncertain climate stabilization scenarios. Furthermore, the observation is that improved efficiency in biomass or CCS has little or no impact on abatement cost implies that policies should prioritize cost control over improving efficiency.

Solar's limited impacts and high performance CPLs point to the need to look beyond the cost of the technology itself when formulating solar energy policy. Policy makers may need to turn their attention instead to other areas, such as improving the performance of storage or the robustness of the grid to non-dispatchable generation. These results should be taken with caution, however, because our constraints on the amount of technological change after 2030 affected solar to a greater degree than any other technology.

This study also highlights the need for further research into the role socioeconomic factors play in the evolution of the supply side of the energy sector. Our results are sensitive to socioeconomic assumptions, especially in high population, low GDP scenarios, but the relative roles of population and GDP are not clear. Further research to better define the individual roles of population and GDP will inform the important question of whether it is more important to stimulate economic growth (and increase the resources available) or control population (and reduce the size of the problem).

Moving forward this work can serve as the basis for additional research into the impact of low carbon energy. While these results provide a what-if analysis for the impact of these parameters, they do not consider the likelihood of reaching any given level of performance; adding probability information could provide important insight.

Additionally, this research considered each parameter separately. In several cases, such as the bioelectric and CCS parameters, there may be strong interaction effects (e.g. between the cost and efficiency of a specific technology), and additional research into these possible interactions and their effects may reveal additional insights. Finally, the different results obtained under the relatively less wealthy socioeconomic scenarios, where sub-optimal policy “mistakes” could be most costly, points to the potential value of additional analysis of the impact of socioeconomics on these results.

CHAPTER 3

IMPACT OF ENERGY TRANSFORMATION PATHWAY ASSUMPTIONS ON THE OPTIMAL R&D PORTFOLIO ALLOCATION FOR LOW CARBON ENERGY TECHNOLOGIES

3.1. Introduction

In Chapter 2 we have developed a methodology for characterizing the impact of a given LCES technology parameter on the cost of achieving a climate target. We applied this methodology to the energy technology menu developed in the TEaM project (1.3.3), using the GCAM model (2.1.3) and the New Scenario Framework (2.1.1). This methodology provided insights into the performance of individual parameters and allowed us to develop qualitative policy recommendations. This chapter builds upon this methodology by attaching probabilistic information to the EDS. The addition of probabilities allows for optimization, which in turn allows for quantitative, rather than qualitative policy analysis.

In addition to extending the methodology of chapter 2 we also examine the problem from a slightly different perspective. Although we again use the TEaM data set as the basis for our analysis, we conduct a sensitivity analysis across energy system assumptions, rather than socioeconomic ones. We also use a different model, the Model for Energy Strategy Alternatives and their General Environmental Impact (MESSAGE), developed and maintained at the International institute for Applied Systems Analysis (IIASA) (Messner, Strubegger 1995).

Our purpose in doing this is twofold. First, it demonstrates the flexibility of the EDS and our methodology. Secondly, it offers the opportunity to examine how the value of energy supply technology R&D is affected by other parts of the energy system, such as the level and nature (e.g. liquid fuels vs. electricity) of demand. This is an important question because research has indicated that investing in demand side measures (e.g. energy efficiency) has far higher returns to investment than supply side measures (Gallagher et al. 2012, Wilson et al. 2012), and characterizing the robustness of supply side R&D investment policy will inform the question of how best to invest in the energy system as a whole.

The balance of this chapter is organized as follows: section 3.2 introduces the model and scenario framework we use in this chapter. Section 3.3 outlines the scenarios developed for our analysis and the methodologies new to this analysis. Section 3.4 discusses our results, and we conclude with a discussion of the policy implications of our work in section 3.5.

3.2. Background

3.2.1. MESSAGE-MACRO

For this exercise, we use the MESSAGE-MACRO model. MESSAGE-MACRO is a variant of MESSAGE that links MESSAGE, an energy systems model, and MACRO, a macroeconomic model. The resulting linked model is intended to capture the influence of energy supply costs on the macro economy. MESSAGE-MACRO is described in detail in Messner, Schrattenholzer (2000). Here we provide an overview of those features of MESSAGE-MACRO most relevant to this work.

MESSAGE is maintained by the International institute for Applied Systems Analysis (IIASA). MESSAGE is described as *"a systems engineering optimization model used for medium- to long-term energy system planning, energy policy analysis, and scenario* *development."* (Riahi et al. 2012). MESSAGE is disaggregated into 11 global regions and models the world's energy system in detailed bottom up fashion, including resource extraction, trade, conversion, transportation, distribution, and end use. MESSAGE minimizes the total system cost subject to exogenous assumptions about population, energy demand, and technological progress (Riahi, Gruebler & Nakicenovic 2007a, Messner, Schrattenholzer 2000).

As an energy systems model, the central set of assumptions is contained within the Reference Energy System (RES). The RES defines the performance, availability, and cost information for the energy system. The major categories of the RES are the primary energy sources (e.g. coal, oil, nuclear, etc.), conversion technologies, and final energy carriers (e.g. electricity, liquid fuels, district heat) (Messner, Schrattenholzer 2000).

The dynamics of global change are modeled in MESSAGE via a linkage to the Model for Greenhouse Gas Induced Climate Change (MAGICC) model (Riahi et al. 2012). MAGICC is a coupled gas cycle/climate model that generates projections for atmospheric GHG concentrations, climate forcing, and oceanic thermal expansion (Wigley 2008).

Land use is represented in MESSAGE by the use of exogenously supplied cost curves for land use emissions and afforestation (Kriegler et al. 2015b). Similarly, bioenergy potentials are supplied through exogenous supply curves.

MACRO is a macroeconomic model developed from the Model for Evaluating Regional and Global Effects of GHG reduction policies (MERGE) (Manne, Mendelsohn & Richels 1995). MACRO maximizes the intertemporal utility of a single representative agent in each world region. The primary variables in MACRO are capital stock, labor, and energy, which determine economic output according to a nested Constant Elasticity of Substitution (CES) function (Messner, Strubegger 1995). MACRO's output is a sequence of optimal savings, investment, and consumption decisions, including final energy demands. MESSAGE-MACRO links these two models.

Figure 9 illustrates the MESSAGE-MACRO solution process. In a MESSAGE-MACRO run, MESSAGE first optimizes the system costs for a starting scenario. The results of the MESSAGE run are converted into cost functions for each energy category, world region, and time period. MACRO then optimizes demands according to these inputs. The optimal demands from MACRO are then used as the input for the next MESSAGE run. This process is repeated until the solution converges (Messner, Schrattenholzer 2000).

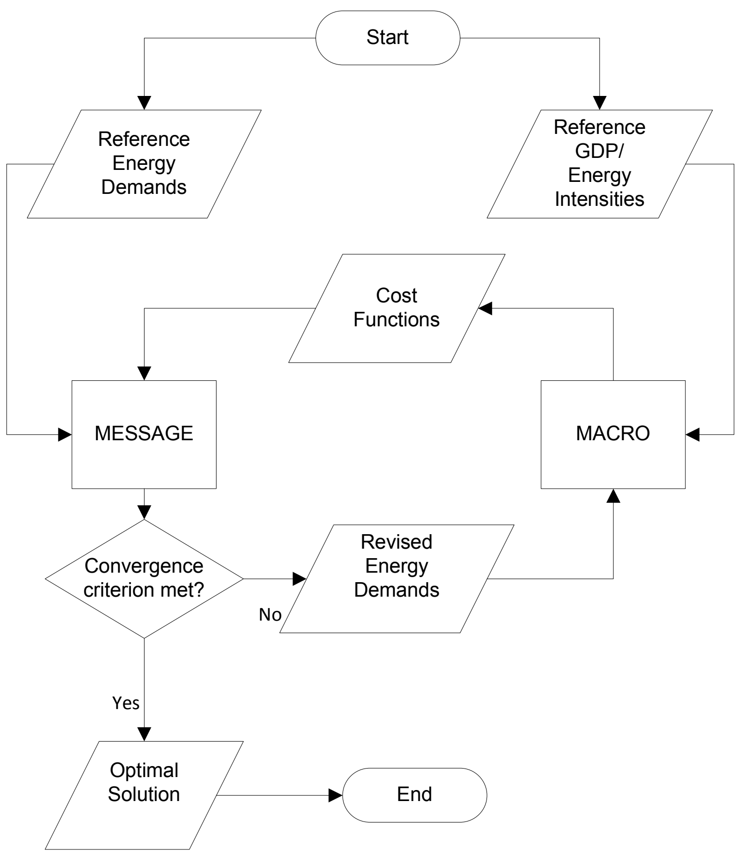


Figure 9: Schematic representation of the MESSAGE-MACRO solution process. Adapted from (Messner, Schrattenholzer 2000).

3.2.2. The Global Energy Assessment Scenario Framework

The Global Energy Assessment (GEA) (GEA 2012b) was established in 2006 to conduct a comprehensive scientific assessment of the global energy system and provide an in-depth examination of energy-related global challenges. The GEA takes a holistic approach to global energy challenges, including climate change, sustainability, and energy access. The GEA examined a number of possible transition scenarios covering different possible socioeconomic, climate, and energy system transitions. This work adopts these GEA scenarios as the basis for our study. They are described in detail in Chapter 17 of the GEA (Riahi et al. 2012). Here, we briefly outline the elements of these scenarios most relevant to this chapter.

3.2.3. Socioeconomic Scenarios

The GDP pathway is based on an updated version of the IPCC B2 scenario projection by Riahi, Gruebler & Nakicenovic (2007b). Global GDP closely follows the SSP1 trajectory until diverging upward at mid-century, ending at a level of approximately 350 trillion 2010 USD in 2100. It is important to note that this is a reference pathway – GDP is subject to adjustment in the MESSAGE-MACRO optimization process.

The population pathway is based on (United Nations Department of Economic and Social Affairs 2009). Population closely follows the SSP2 pathway, with population peaking at roughly 9.5 billion around 2075 before declining.

Figure 10, Figure 11, and Figure 12 show the population and GDP pathways in comparison to the corresponding SSP pathways used in the previous chapter.

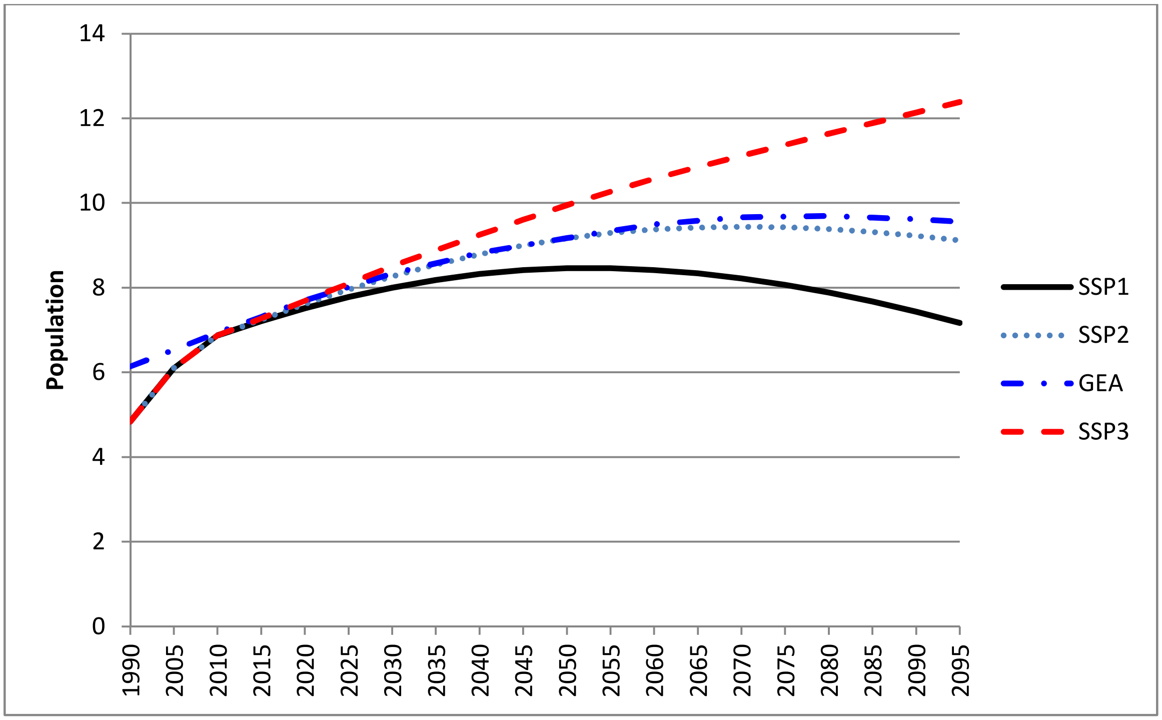


Figure 10: GEA Population pathway compared to SSPs 1-3.

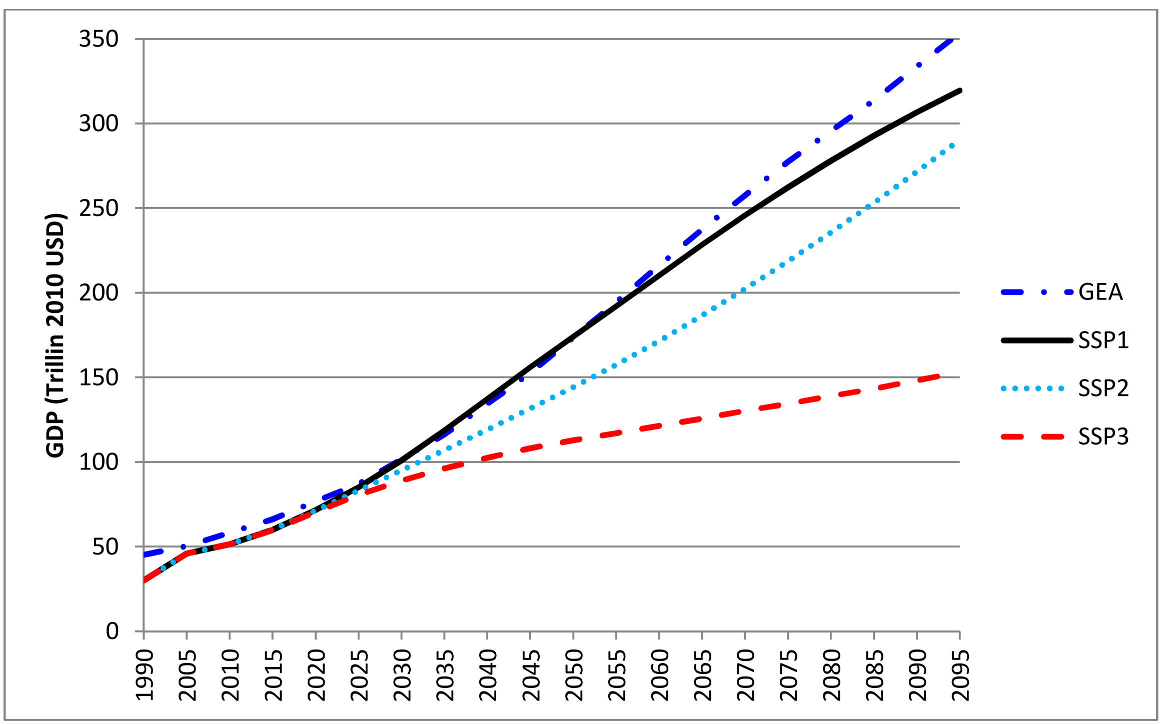


Figure 11: GEA GDP pathway compared to SSPs 1-3.

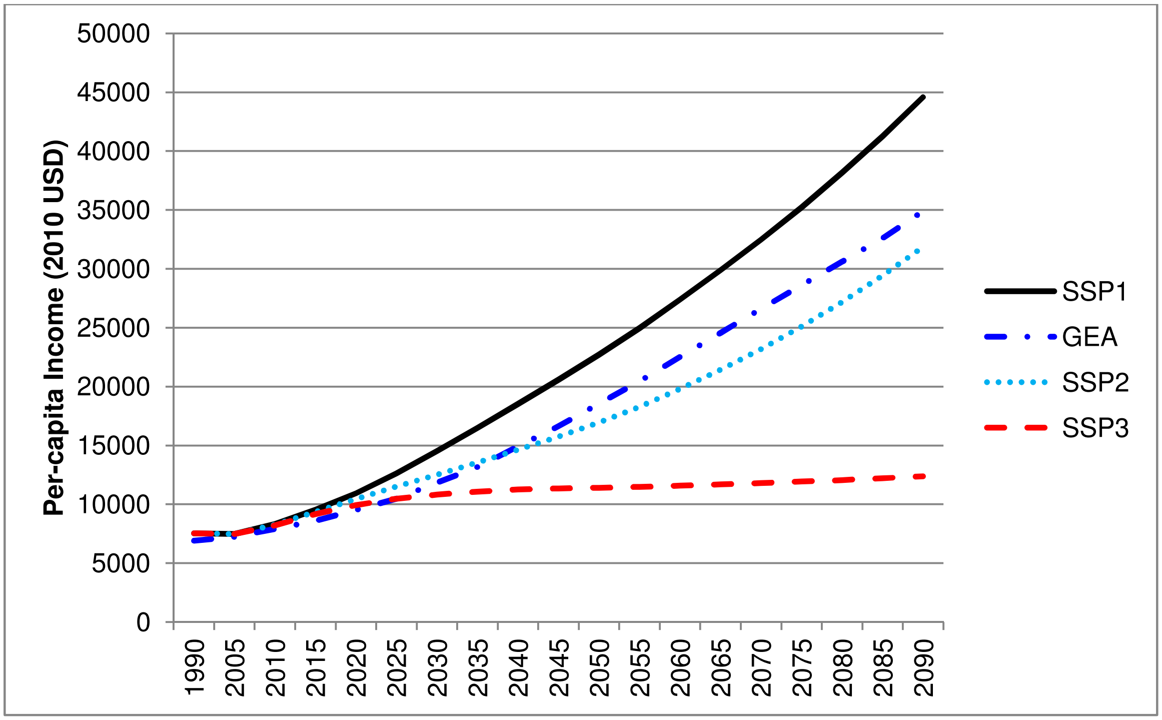


Figure 12: GEA per-capita GDP pathway compared to SSPs 1-3.

3.2.4. Technology Scenarios

The GEA examined a number of possible pathways that the energy system could follow in the 21st century (energy pathways). These energy pathways are categorized according to three "branching points" corresponding to significant choices about the energy system that lead to divergent outcomes: the level of demand for energy, type of transportation system (e.g. electric vs liquid fueled), and the composition of the energy supply technology portfolio.

The first branching point, efficiency, characterizes the level of emphasis placed on demand-side changes (Riahi et al. 2012). The low demand scenario (GEA – Efficiency) assumes comprehensive demand side measures to increase energy efficiency, resulting in low energy demand. The high demand scenario (GEA - Supply) assumes limited demand side measures, with consequently high energy demand. The intermediate demand scenario (GEA – Mixed) assumes an intermediate level of demand side measures and energy demand.

The second branching point is the type of transportation system. The GEA offers two choices of transportation system: a "conventional" system relying on liquid fuels, and an "advanced" system utilizing electric or hydrogen powered vehicles.

Finally, the third branching point is the evolution of the supply side portfolio. Different options within the third branching point correspond to different supply side configurations. For example, limits on nuclear energy, or the availability of biomass, CCS, or other specific technologies would all represent different choices at the third branching point. Figure 13 is a schematic representation of these branching points. Due to the numerous possible combinations of the supply side portfolio the third branching point is the most complex of the three. The GEA examined a total of ten different supply side portfolio restrictions.

For this exercise, biomass was selected from among the supply side technologies for special scrutiny because of its unique characteristics. Biomass is unique among low carbon energy supply technologies because it has the potential to be carbon-neutral (or nearly so), but is also orders of magnitude more water intensive than conventional fossil fuel technologies and competes with food crops for land (Finley, Seiber 2014). Moreover, there are concerns that widespread deployment of biomass may adversely impact food security in the developing world (Coelho et al. 2012, Dornburg et al. 2010).

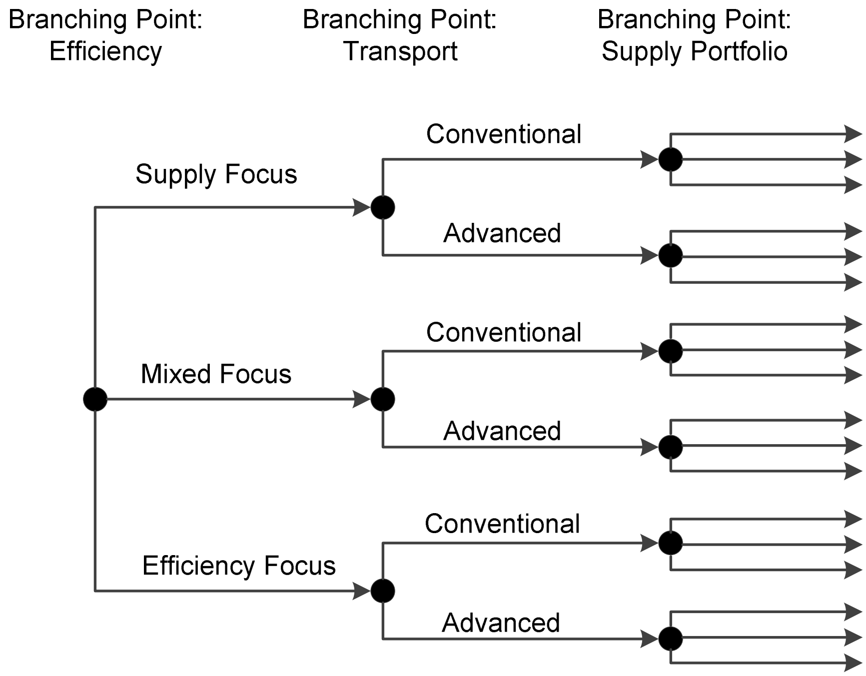


Figure 13: Illustration of future energy pathways and branching points (adapted from (Riahi et al. 2012)).

3.2.5. TEaM Probability and Investment Levels

In section 2.1.2 we introduced the Elicitation Data Set (EDS). Recall that the EDS $\boldsymbol{X}$ contains 1000 States of the World (SOWs) $\boldsymbol{x}_i$, and each SOW is composed of eight elements x_{ij}, each of which corresponds to a particular value of one of the technology parameters.

In addition to these parameter values the EDS also contains probability information. The TEaM project produced a probability distribution for each parameter and institution (including all three combined), and investment level (Baker et al. 2015). In this work we will use only the probability distributions and funding levels for all three institutions combined.

Let $l_j = \{Low, Mid, High\}$ be the level of funding in the technology associated with parameter j and $p(x_j|l_j)$ be the probability distribution for parameter j given investment level l. In what follows we will refer to these probability distributions as *nominal distributions*.

It is necessary to distinguish between the technologies which are the target of R&D investment, and the parameters whose value is affected by those R&D investments. This is because R&D investments are made in technologies rather than parameters. That is, it is not possible to direct funding to efficiency or cost, but only to the technology as a whole. For example, it is not possible to fund CCS Cost at the high level and CCS efficiency at the low level – both CCS Cost and CCS efficiency would have to be funded at the same level – high/high, mid/mid, or low/low. The same is true for bioelectricity and bioliquids. Table 6 below summarizes the relationship between technologies and parameters and the nomenclature we will use to make this distinction.

Table 6: Nomenclature.

Technology	Technology Code	Parameter	Short Name	Parameter Code
Solar	SOL	Solar Levelized Cost of Eletricity	Solar	SOL
Nuclear	NUC	Nuclear Overnight Capital Cost	Nuclear	NUC
Bioliquids	BL	Bioliquids Non Energy Cost	Bioliquids Cost	BLC
		Bioliquids Efficiency	Bioliquids Efficiency	BLE
Bioelectricity	BE	Bioelectricity Non Energy Cost	Bioelectricity Cost	BEC
		Bioelectricity Efficiency	Bioelectricity Efficiency	BEE
CCS	CCS	CCS Additional Capital Cost	CCS Cost	CSC
		CCS Energy Penalty	CCS Efficiency	CSE

The investment levels for each individual technology are summarized in Table 7 below, which is derived from Table 4 in Baker et al. (2015). In order to maintain consistency with Baker et al. (2015)'s practice for generating combined probability distributions we calculate the combined investment as the average of the UMass, FEEM, and Harvard investments.

Table 7: R&D investment levels (Millions of $2010/year).

	Nuclear	Solar	Bioelectricity	Bioliquids	CCS
Low	578	134	110	109	569
Mid	1,292	269	199	249	1,149
High	11,984	2,217	1,138	1,366	11,304

3.2.6. Importance Sampling

Sensitivity analysis across institutions or funding requires calculating expectations across multiple nominal distributions. One way to accomplish this would be to generate multiple Monte-Carlo samples, one from each distribution of interest, and perform separate model runs with each of these samples. The computational intensity of the IAMs being used in this exercise make this approach impractical. In order to reduce the overall computational burden we use the technique of importance sampling to allow us to use a single set of parameter samples (the EDS) and model runs to analyze different funding and institutional scenarios.

The technique of importance sampling was originally developed in order to address the problem of performing Monte Carlo analysis in situations where the distribution of a parameter has a low probability of occurrence. In such situations sampling directly from the nominal distribution could require impractically large sample sizes. Importance sampling allows for sampling from a distribution more favorable to the area of interest and then renormalizing back to the actual distribution (Owen, Zhou 2000).

In importance sampling, samples are drawn from an *importance distribution* $q(x)$ that favors the area of interest, and then renormalized back to the nominal distribution using the likelihood ratio $\frac{p(x)}{q(x)}$. While this technique has traditionally been used as a variance reduction technique, we apply this technique to allow us to weight a single set of model runs to any of our nominal distributions.

This application of importance sampling confers two important benefits: (1) it allows us to use a single set of model runs to analyze any of our R&D funding scenarios, and (2) it allows us to quickly revise our results if new information becomes available (and changes our nominal distributions).

3.2.7. The Critical Performance Level and Effect Size

In section 2.2.3. we introduced the Critical Performance Level (CPL), the minimum performance level that a given parameter must achieve in order to have a statistically significant effect on the model output. We again use the CPL in this chapter.

In addition to measuring the significance of a parameter's effect, it is also useful to measure the magnitude of that effect. This is because measures of significance such as the t statistic allow conclusions about the *existence* of an effect but they give no information about its strength: it is possible that a parameter may have a statistically significant but very small impact, which would be of little practical value.

In chapter 2 we used a simple measure of impact magnitude based on the percentage difference in mean policy cost (see section 2.2.3 for details). While this metric provides some insight into the magnitude of a parameter's impact it does not consider the variance of the data. In this chapter we use Cohen's d (Cohen 1977) as our measure of effect size. Cohen's d has the advantage of incorporating variance information and is given by:

$$d = \frac{\bar{w}_1 - \bar{w}_2}{s}$$

where $\bar{w}_1$ and $\bar{w}_2$ are the means of the groups being compared and s is the pooled standard deviation of the data. Cohen's d is a dimensionless number. Higher absolute values indicate a larger effect.

3.3. Methods

In the following sections we present our R&D portfolio optimization model. We first present the model, and then explain its construction.

3.3.1. R&D Portfolio Optimization Model

Our R&D portfolio optimization model maximizes the payoff of R&D. The objective function is given by:

$$\max_{\boldsymbol{l}_g} R_g$$

s.t

$$l_{BEC} = l_{BEE}$$

$$l_{BLC} = l_{BLE}$$

$$l_{CSC} = l_{CSE}$$

$$c_g \leq B$$

where R_g is the payoff of R&D investment portfolio $\boldsymbol{l}_g$, c_g is the cost of investment portfolio $\boldsymbol{l}_g$, and B is the budget constraint . The three constraints on the elements of $\boldsymbol{l}_g$ ensure that parameters of the same technology have the same investment level (see section 3.2.5). We describe the definition of the payoff R_g in Section 3.3.3, and the definition of the investment portfolio $\boldsymbol{l}_g$ in section 3.3.2.

3.3.2. Investment Portfolios and R&D Budget Levels

We construct investment portfolios based on the funding levels and technologies in the EDS. Let $\boldsymbol{l}_g = \{l_{NUC}, l_{SOL}, l_{BLC}, l_{BLE}, l_{BEC}, l_{BEE}, l_{CSC}, l_{CSE}\}$ be an *investment portfolio* that represents some combination of investments. There are a total of three levels of investment across each of five technologies for a total of $3^5 = 243$ valid investment portfolios.

The structure of the R&D investment levels causes the portfolios to fall into three groups as illustrated in Figure 14. In accordance with this grouping, we define budget levels at 10, 20 , and 30 billion 2010 USD per year, which we will refer to as the "low", "mid", and "high" budget levels, respectively. These *budget* levels are not to be confused with R&D *investment* levels. For example, at the low budget level of 10 billion dollars per year it is still possible to choose high investment in solar energy, which costs only 2.2 billion dollars per year.

Ideally we would compare our investment portfolios under these budget levels to a zero-investment baseline. This is not possible here because the EDS does not contain information about technological progress under zero investment. Therefore we define our baseline investment portfolio $\boldsymbol{l^o} = \{Low, Low, \ldots, Low\}$ as the lowest possible investment (1.434 Billion 2010 USD/year), corresponding to investing at the low level in all technologies.

It should be noted that this restriction on the minimum level of investment prevents us from distinguishing, on the basis of investment alone, between investments with no value at all and those that have value only at the low level. For example, if an optimal investment portfolio calls for low investment in CCS this could be because CCS has no value, or because the gains available at mid and high investment are not cost effective. It may, however, be possible to infer which situation is occurring by considering other factors. For instance, in the case of CCS, the absence of a carbon policy implies that low investment reflects a lack of value, since CCS can only be cost effective within the context of a carbon policy.

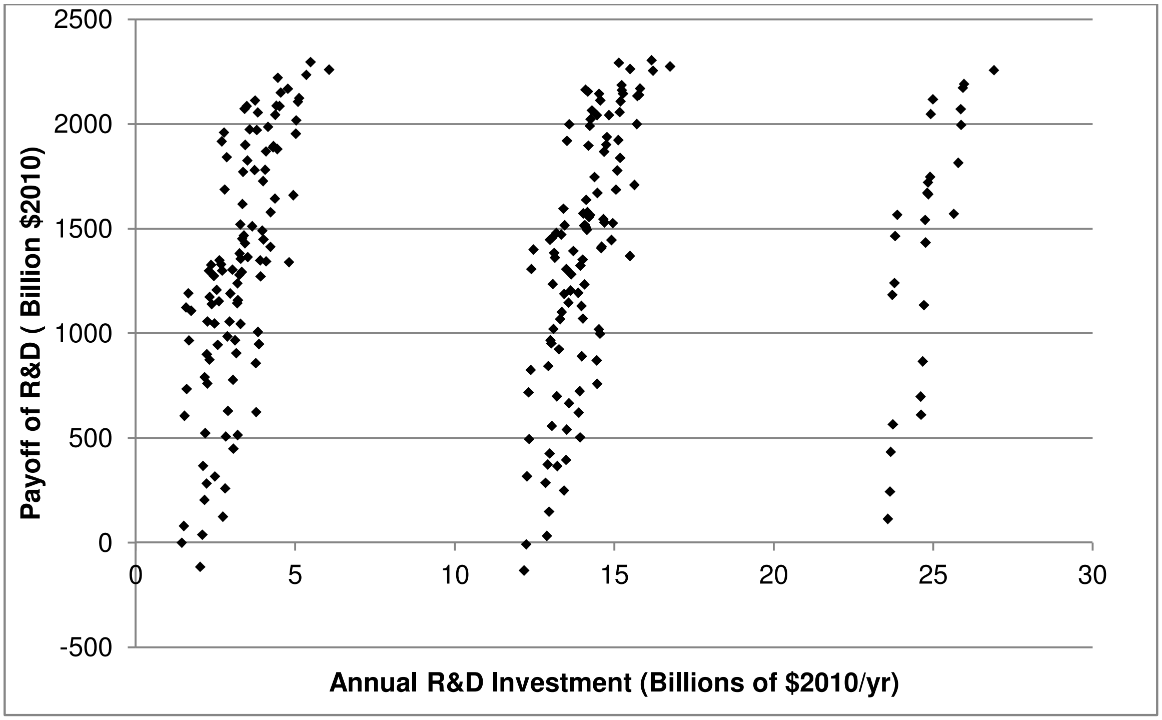


Figure 14: Scatterplot of R&D portfolios by investment level and benefit of R&D in the unconstrained case.

3.3.3. The Payoff of R&D

We define the "payoff of R&D" as the change in expected consumption for a given R&D investment portfolio, compared to the baseline R&D portfolio. The expected consumption w_g for investment portfolio $\boldsymbol{l}_g$ is a weighted average of each SOW's consumption w_i weighted by its likelihood.

The likelihood $p(\boldsymbol{x}_i|\boldsymbol{l}_g)$ of SOW $\boldsymbol{x}_i$ given some investment portfolio $\boldsymbol{l}_g$ is given by

$$p(\boldsymbol{x}_i|\boldsymbol{l}_g) = \prod_{j=1}^{8} p(x_j|l_j)$$

These likelihoods are then normalized by dividing by the sum across all samples to get a weight $v_{\boldsymbol{l}_g}(\boldsymbol{x}_i)$

$$v_{\boldsymbol{l}_g}(\boldsymbol{x}_i) = \frac{p(\boldsymbol{x}_i|\boldsymbol{l}_g)}{\sum_i p(\boldsymbol{x}_i|\boldsymbol{l}_g)}$$

which is used to calculate the expected consumption as follows:

$$w_g = \sum_i v_{\boldsymbol{l}_g}(\boldsymbol{x}_i)\, w_i$$

The payoff R_g of R&D investment portfolio $\boldsymbol{l}_g$ is calculated by subtracting the expected consumption under the baseline investment portfolio from the expected consumption w_g:

$$R_g = w_g - w^o$$

where w^o is the expected consumption under the baseline investment portfolio. This represents the consumption loss avoided by making investment $\boldsymbol{l}_g$.

We also define the return of R&D investment. The return r_g of R&D investment is given by:

$$r_g = \frac{R_g}{c_g}$$

where the cost c_g of an investment portfolio is the discounted sum of the investments in each technology over a ten year period, discounted at 5%.

It will be useful to consider both of the above metrics not only in terms of total investment, but also in terms of incremental investment. The incremental payoff (return) of investment is similar to the concept of a marginal payoff (return) in that it represents the impact from an additional unit; however, we use the term “incremental” to underscore the point that in this case the “units” of investment (the cost of the investment portfolios) are non-uniform and discrete. That is, the portfolio investments are lumpy – there is no partial investment into an individual project – and the difference in the cost between an investment portfolio and the next most expensive portfolio is not uniform across the portfolios.

When discussing the incremental payoff or return to investment we will discuss only the optimal case. Let R^*_{Low}, R^*_{Mid}, and R^*_{High} be the maximum payoffss for the low, mid, and high budget levels, respectively. Similarly, we use r^*_{Low}, r^*_{Mid}, and r^*_{High} to designate the corresponding return.

In the low budget case the incremental payoff $\bar{R}^*_{Low}$ is equal to the payoff R^*_{Low}. The incremental payoff $\bar{R}^*_{Mid}$ achieved by moving to the mid budget level from the low budget level is given by:

$$\bar{R}^*_{Mid} = R^*_{Mid} - R^*_{Low}$$

$\bar{R}^*_{High}$ can be calculated in a similar manner.

The incremental return can also be defined for each budget level. The incremental return achieved by moving to the low budget level from the base budget is given by:

$$\bar{r}^*_{Low} = \frac{\bar{R}^*_{Low}}{c^*_{Low} - c^*_{Base}}$$

The incremental return for the mid and high budget levels are defined similarly.

3.3.4. Sensitivity Cases

This work uses the GEA scenario framework as a starting point to construct scenarios to serve as the basis for our sensitivity analysis. These sensitivity cases are chosen to correspond to the three branching points discussed in section 3.2.2. In addition to the branching points we also consider the impact of the carbon constraint. We construct a total of six sensitivity cases. Table 8 gives a summary of each scenario's assumptions.

3.3.4.1. Unconstrained

The unconstrained case uses the GEA-Mix demand scenario, coupled with the conventional transportation system and standard biomass availability. This scenario assumes no carbon policy.

3.3.4.2. 3.0 w/m² Peak and Decline (3.0 PD)

The 3.0 PD scenario uses the GEA-Mix demand assumptions, conventional transport, and standard biomass availability under a 3.0 w/m^2 peak-and-decline forcing constraint, where radiative forcing is constrained to 3.0 w/m^2 in 2100 but allowed to exceed this figure mid-century.

Radiative forcing constraints are an alternative to the concentration method of constraining carbon emissions. Instead of limiting carbon emissions directly, forcing constraints limit radiative forcing, which is a function of greenhouse gas concentration. Either approach will have the effect of reducing greenhouse gas emissions.

3.3.4.3. 3.7 w/m^2 Peak and Decline (3.7 PD)

3.7PD is identical to the 3PD scenario, except that it imposes a looser 3.7 w/m^2 peak-and-decline carbon constraint. This scenario was selected to highlight the impact of a looser carbon constraint.

3.3.4.4. Advanced Transportation (Adv Trp)

The Adv Trp scenario uses the GEA-Mix demand assumptions, a 3.0 w/m^2 forcing constraint, and standard biomass availability, but allows a more electrified transportation network. In the conventional transport scenario transport electrification becomes available in 2010 and is limited to 35-50% of transportation energy demand, depending on the region. The advanced transportation scenario also allows electrification beginning in 2010 but allows up to 75% of transport energy demand to be supplied by electricity.

3.3.4.5. Low Biomass Availability (Low Bio)

This scenario uses a 3.0 w/m^2 forcing constraint, and a standard transportation system, but restricts the availability of biomass feedstocks. This represents a world where competition for food (or other factors) restricts the quantity of biomass feedstocks available for energy production to 50% of the standard biomass level (Riahi et al. 2012).

3.3.4.6. Low Energy Intensity (LEI)

The LEI scenario adopts the GEA-Low demand assumptions, conventional transport, standard biomass, and a 3.0 w/m^2 forcing constraint. This scenario was chosen to highlight the tradeoffs between supply and demand-side measures.

The GEA-Mix and GEA-Low scenarios were chosen for the efficiency dimension. These scenarios were chosen to examine how reduced demand impacts the value of supply side R&D.

Table 8: Summary of sensitivity cases.

Scenario	Transport	Demand	Biomass Availability	Climate Constraint
Unconstrained	Regular	GEA-Mix	High	None
3.7PD	Regular	GEA-Mix	High	3.7 w/m^2
3PD	Regular	GEA-Mix	High	3.0 w/m^2
Advanced Transport	Advanced	GEA-Mix	High	3.0 w/m^2
Low Energy Intensity	Regular	GEA-Low	High	3.0 w/m^2
Low Biomass	Regular	GEA-Mix	Low	3.0 w/m^2

3.3.5. Generating Technology Inputs

The technology inputs were generated in a similar manner to those used in Chapter 2. The elicited data was converted into MESSAGE units, and then used to generate cost curves for the appropriate input parameters in MESSAGE.

While the overall strategy is the same, structural differences between the MESSAGE and GCAM energy systems necessitated slightly different techniques. Unlike the conversions for GCAM inputs, none of the MESSAGE inputs were trivial unit conversions. In order to maintain compatibility with the other Team data, solar used the capacity factor, lifetime, and discount rate figures from Baker et al. (2015). Bioliquids cost, bioliquids efficiency, bioelectricity cost, and bioelectricity efficiency required assumptions about the Lower Heating Values (LHV), Higher Heating Values (HHV), and the energy content of a Gallon of Gasoline Equivalent (GGE). Here we used values published by the Oak Ridge National Laboratory (Boundy et al. 2011). Both bioenergy technologies required an additional assumption of a 90% capacity factor.

The remaining parameters, CCS cost and CCS energy penalty, are not explicit input parameters in MESSAGE. In these cases we make the assumption that these parameters represent the difference between the cost and/or efficiency of coal with and without CCS. We also assume that the relative cost and efficiency of coal and other technologies with a CCS option (e.g. gas, biomass) under the MESSAGE default assumptions remain the same for the TEaM data and adjust the other CCS technologies accordingly. For example, if the cost of biomass CCS is double the cost of coal CCS in a given period in the MESSAGE default assumptions, we assume that the cost of biomass CCS is double that of coal CCS in that period, regardless of the underlying elicitation values.

3.4. Results and Discussion

3.4.1. Critical Performance Level and Effect Size

As in Chapter 2, we calculate the CPL and effect size, except that here we use *Cohen's d* as our measure of effect size, rather than the simple percentage impact used in chapter 2. We see a similar trend in these results as we did in chapter 2: there is a clearly dominant parameter, a parameter that has no significant effect, and some parameters have CPLs in only some of the sensitivity cases. The results of this exercise differ, however, in which technologies are important.

Recall that when a CPL is "high-performance" this means that it has a very favorable value (high efficiency or low cost). Conversely, "low-performance" CPLs have unfavorable values (low efficiency or high cost). A low performance CPL indicates that a parameter will have a significant effect at low performance levels, which may make R&D more attractive since smaller performance gains would be required to realize a payoff. On the other hand, a high performance CPL may make R&D riskier since only significant performance gains would pay off.

Table 9 summarizes CPL and effect size results. Only one parameter, CCS efficiency, never has a CPL. The only parameter with a CPL in all scenarios is bioliquids efficiency; the CPL is at the low performance end of the range in all but the low bio scenario, where it is near the middle of the test range. Nuclear has a CPL in only one scenario – 3.7 PD, and it is at the extreme high performance end of the test range. Solar does not have a CPL in the 3.0 PD or 3.7 PD scenarios, but it does in all of the others. When solar is significant it has a CPL of ~ $0.20/kWh, which is already achievable in certain areas. Bioliquids cost is significant in all scenarios except low bio, but at <$1/GGE the CPL is at the high performance end of the test range. Bioelectricity cost has a CPL in all scenarios except 3.7PD, but just as with many of the other technologies, the CPL is at the high performance end of the range (\$0.02 – 0.04 / kWh). Bioelectricity efficiency is significant in all but two scenarios, and its CPL falls near the middle of the test range.

While most parameters are significant, their effect size varies considerably. Bioliquids efficiency has by far the strongest impact: in all scenarios except Low Bio d values range from ~1.9 – 2.2 - several orders of magnitude higher than the other parameters. CCS cost's impact is second only to bioliquids efficiency with a d value around 0.1. Solar has a d value of ~0.06. Bioelectricity cost and efficiency have d values in the range of -0.01, and bioliquids cost has a significantly lower impact at around 0.001-0.002, an order of magnitude smaller than even the next lowest impact value.

Table 9: CPL and Effect size.

CPL								
	BEE %	BEC $/kWh	BLE %	BLC $/GGE	CSC $/kW	CSE %	NUC $/kW	SOL $/kWh
3PD	47.53	0.025	23.20	0.84	-	-	-	-
3p7PD	-	-	23.20	0.86	-	-	857	-
AdvTrp	47.92	0.024	23.20	0.87	1558	-	-	0.214
LEI	42.19	0.039	23.20	0.90	1702	-	-	0.205
LowBio	-	0.038	41.56	-	-	-	-	0.210

Effect Size								
	BEE	BEC	BLE	BLC	CSC	CSE	NUC	SOL
3PD	-0.010	-0.015	2.128	0.001	-	-	-	-
3p7PD	-	-	1.861	0.002	-	-	0.009	-
AdvTrp	-0.009	-0.018	1.984	0.001	0.082	-	-	0.067
LEI	-0.013	-0.020	2.192	0.002	0.127	-	-	0.056
LowBio	-	-0.016	0.069	-	-	-	-	0.058

The overall picture painted here is that when biomass feedstocks are available bioliquids have a great potential to reduce the cost of climate mitigation, while the other technologies play much smaller roles (if any). The only exception to the pattern is the Low Bio scenario, when bioliquids have impacts comparable to the other technologies.

While these results make it clear that biofuels have a dominant effect the underlying reason is less obvious. Biomass feedstocks are nearly carbon neutral and can be used in existing transportation infrastructure, so they may offer an economical alternative to alternatives such as transport electrification. Additionally, by reducing net emissions in sectors such as aviation, where there is no viable alternative to liquid fuels, biofuels may avoid the need to offset those emissions with more costly abatement in non-transportation areas.

The behavior of the bioelectricity technologies is noteworthy because of the negative *d* value. In our results a negative *d* value indicates an inverse relationship between performance and consumption – that is, improving a parameter's performance will lead to reduced consumption. There are several possible explanations for this behavior: this may be a paradoxical effect, it may be a modeling artifact, or it may be a consequence of our data. Additional diagnostic work is required to determine the exact cause.

There is a stark dichotomy between bioenergy and the other technologies. This can be seen by comparing the columns of Table 9. The left four columns are the bioenergy parameters, and most cases show a CPL. On the other hand, the right four columns are the non-biomass technologies; in most cases these technologies have no CPL.

Another important observation is that although CCS cost is significant in some scenarios CCS efficiency never is. This may be due to the fact that fossil fuel supplies, especially coal, are relatively abundant, so if even if CCS is relatively inefficient there would still be ample fuel available at relatively low cost. This result implies that trading efficiency for cost may be desirable, if such an opportunity was available.

3.4.2. Optimal R&D Portfolios

Recall from section 3.3.1 that an optimal R&D portfolio maximizes the payoff of R&D investment subject to a budget constraint. Table 10 summarizes our optimal portfolios by budget level and sensitivity case. The optimal portfolios are somewhat robust, and in three of the sensitivity cases: 3.0 PD, 3.7 PD, and advanced transport, the optimal portfolios are identical.

Solar is the most robust technology, with high investment across all budget levels and sensitivity cases. Bioelectricity and bioliquids are also robust, with investment invested at the high level in all cases except the Low Bio case.

Nuclear and CCS show the most variability. Nuclear shows a consistent pattern of increasing from mid to high investment as the budget increases, except in the low energy intensity case, where investment is low throughout. CCS shows the most variation, with low investment at all budget levels in the unconstrained case, mid-level investment in the 3.0 PD and 3.7 PD cases, and high investment in the LEI and Low Bio cases.

In all sensitivity cases except Low Bio the optimal portfolios at the mid and high budget levels are identical despite the availability of additional funds for investment. Since our optimization method does not penalize R&D investment we would expect all fund available should be spent. As we will discuss below, when return to R&D is considered this effect is not large enough to affect our results, however; we discuss the underlying cause for the sake of completeness.

The root cause of this phenomenon lies with the method of calculating the likelihood of each SOW. As discussed in section 3.3.3 the likelihood of each SOW is based on a multivariate distribution whose marginal probabilities are each individual parameter's distribution. R&D investment impacts these marginal probabilities. Note that increasing investment in a technology will reduce the likelihood of SOWs in which the technology has a bad outcome.

Consider a SOW with a particularly favorable outcome in a parameter with a large impact, but a particularly bad outcome in a parameter with little or no impact. In the context of our results here this would mean a SOW with very high bioliquids efficiency and very low CCS efficiency. We would expect this SOW to have a favorable outcome (in this case high consumption), and therefore to be desirable. Because the CCS efficiency does not have a CPL it would not affect the payoff, however, R&D investment would affect its probability distribution. In such a case, increasing R&D investment in CCS would make the unfavorable CCS efficiency outcome (and therefore the SOW) less likely, which would reduce that SOW's corresponding weight in the expectation calculation. This is an artifact of the importance sampling, and happens only when a technology's impact (and therefore the expected improvement from increasing R&D investment) is small.

The optimal portfolios described above provide important insight, however they do not paint the whole picture. Our optimization method optimizes according to an exogenous budget constraint. We chose this method because MESSAGE-MACRO is not able to endogenously model the opportunity cost of R&D. Therefore the fact that an investment portfolio is optimal does not mean that it is a good investment; it is also necessary to verify that the payoff is greater than the cost (i.e. the return is greater than one).

Table 10: Optimal R&D portfolios.

	Budget	Technology NUC	SOL	BE	BL	CCS
Unconstrained	Low	Mid	High	High	High	Low
	Mid	High	High	High	High	Low
	High	High	High	High	High	Low
3.0 w/m^2 3.7 w/M^2 Adv Trp	Low	Mid	High	High	High	Mid
	Mid	High	High	High	High	Mid
	High	High	High	High	High	Mid
LEI (High energy efficiency)	Low	Low	High	High	High	Mid
	Mid	Low	High	High	High	High
	High	Low	High	High	High	High
Low Bio	Low	Mid	High	Low	Low	Mid
	Mid	Mid	High	Low	Low	High
	High	High	High	Low	Low	High

The payoff of R&D investment is summarized in Table 11 and

Figure 15. Despite the similarity of the optimal investment portfolios the payoff of R&D varies considerably across the sensitivity cases. The payoff of R&D ranges from ~$2.5 trillion in the unconstrained case to a high of ~ $25 trillion in the Low Bio case.

While the payoff varies considerably across sensitivity cases it changes very little under increasing budgets. In most cases the payoff does not increase at all between the mid and high budget levels. Except for the Low Bio case the largest improvement in the payoff between the low and mid budget levels is 5.2% in the LEI case, while R&D investment increases by nearly 200%. In the Low Bio case the return to investment increases by 42.7% from the low to mid budget levels, while the investment increases by over 250%. These sharply diminishing returns can be seen clearly in Figure 16.

Table 11: Payoff of R&D investment (Billions of $2010).

Budget Level	Unconstrained	3.0 PD	3.7 PD	Adv Trp	LEI	Low Bio
Low	2,549	10,036	5,979	7,230	4,847	17,863
Mid	2,559	10,199	6,110	7,357	5,103	25,499
High	2,559	10,199	6,110	7,357	5,103	25,834

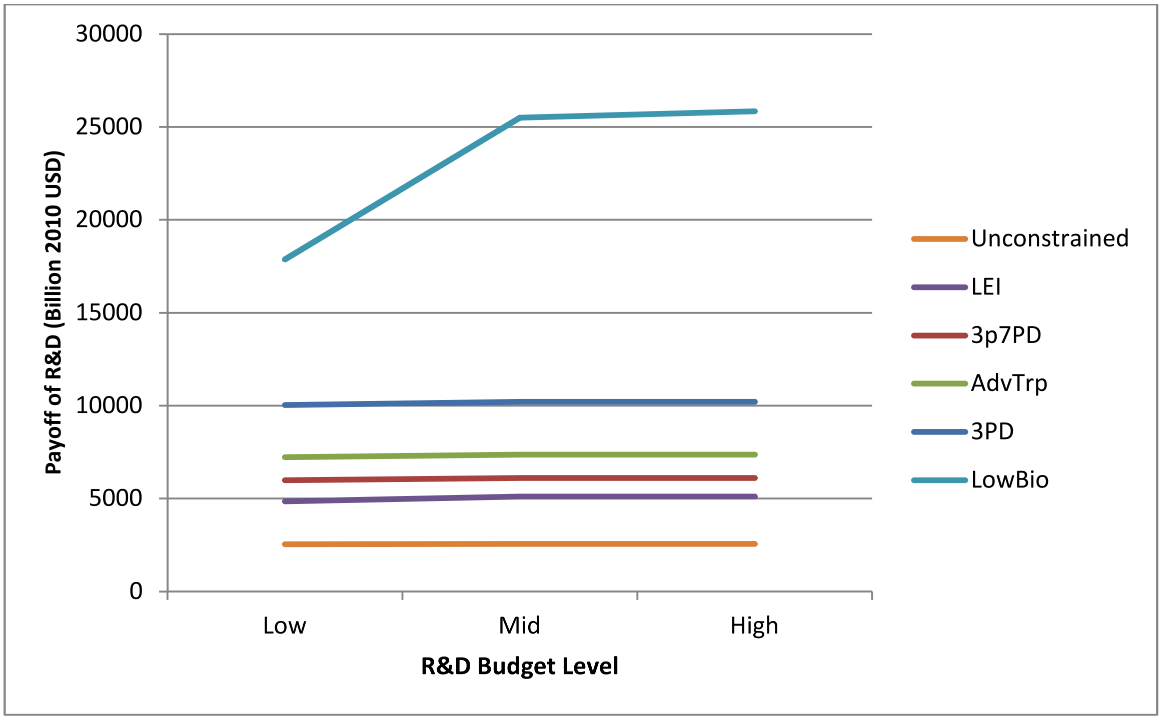


Figure 15: Payoff of R&D investment by budget level.

In order to determine the attractiveness of an investment portfolio we look at the incremental return for each budget level. If an investment portfolio's cost is greater than the payoff it is not attractive. Similarly, if the incremental return is less than one the incremental payoff is less than the incremental cost, which implies that the incremental investment is not attractive.

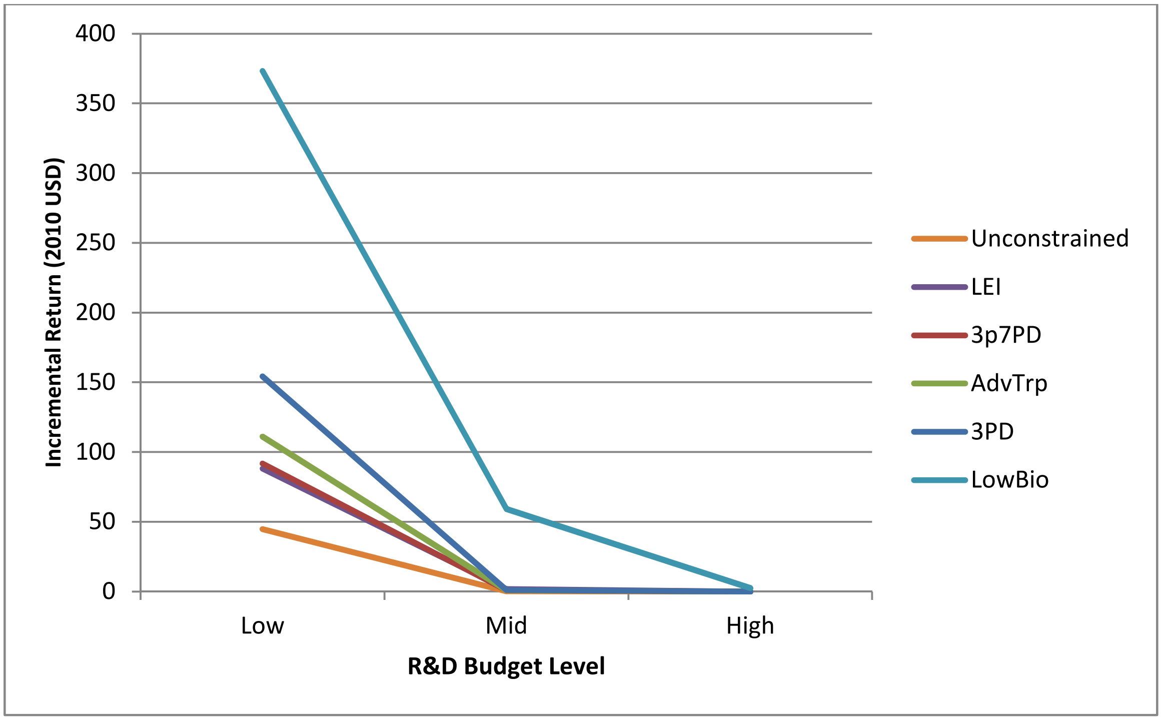


Figure 16: Incremental return to investment.

Table 12 summarizes the return for our optimal portfolios. While the return is attractive under all sensitivity cases and budget levels, the incremental return is often not attractive. For example, in the unconstrained case the payoff under at the mid budget is only $10 billion higher than under the low budget, while the total investment increases by $150 billion, yielding an incremental return of $0.06. Since return and incremental return are the same at the low budget level, the low budget portfolio investment is attractive in all sensitivity cases, including the unconstrained case. The only cases that have attractive incremental returns at the mid budget level are 3.0 PD, LEI, and Low Bio. Only Low Bio has an attractive incremental return at the high budget.

Table 13 summarizes the optimal attractive portfolios. The attractive budget level is sensitive to our sensitivity cases. The optimal attractive budget is low for the unconstrained, 3.7 PD, and Adv Trp scenarios, mid for 3.0 PD and LEI, and high for Low

Bio. In all cases the increased spending goes to nuclear and CCS. Under the LEI case CCS is funded preferentially to nuclear. These portfolios also show that the value of bioenergy R&D is dependent on the supply of biomass.

Table 12: Return and incremental return for optimal portfolios.

Budget Level		Unconstrained	3.0 PD	3.7 PD	Adv Trp	LEI	Low Bio
Low	Total Return	44.77	154.13	91.82	111.04	88.04	373.25
	Incremental Return	44.77	154.13	91.82	111.04	88.04	373.25
Mid	Total Return	12.32	47.26	28.31	34.09	25.75	144.22
	Incremental Return	0.06	1.08	0.87	0.84	1.79	59.22
High	Total Return	12.32	47.26	28.31	34.09	25.75	82.65
	Incremental Return	0.00	0.00	0.00	0.00	0.00	2.47

Table 13: Optimal attractive portfolios.

	Budget	Technology				
		NUC	SOL	BE	BL	CCS
Unconstrained	Low	Mid	High	High	High	Low
3.7 w/M^2 Adv Trp	Low	Mid	High	High	High	Mid
3.0 w/m^2	Mid	High	High	High	High	Mid
LEI	Mid	Low	High	High	High	High
Low Bio	High	High	High	Low	Low	High

3.5. Conclusions & Policy Implications

These results raise several points: Firstly, it pays to invest even without a carbon constraint. Secondly, we need to take a closer look at bioenergy technologies. Third, we should investigate the value of better information about the energy system, and finally, increasing R&D investment is not always cost effective.

One of the most important observations about these results is that there is value in R&D investment even without a carbon policy. This is because with the exception of CCS, all of the technologies considered could have value in an unconstrained world. In fact, the overall optimal portfolio for the unconstrained case is nearly the same as for every other sensitivity case except Low Bio. The only difference is with CCS, which cannot have value in a no-policy world, and nuclear. The bottom line is that positive returns in an unconstrained scenario indicate that we have nothing to lose – and potentially a great deal to gain - by investing in R&D immediately.

Our results are sensitive to bioenergy technologies in three distinct ways. First, within each sensitivity case the dominant parameter is bioliquids efficiency. Second, our optimal portfolios are fairly robust, except in the restricted biomass case. Finally, the payoff and return of R&D are highest by a wide margin in the restricted biomass case. Taken together, these results call for additional research into the role of bioenergy, both with respect to its behavior in the economy and its representation in models.

While bioenergy technology has the largest role to play, these results also highlight the importance of the demand side of the energy system. Return drops by almost half under the LEI scenario, compared to the 3.0 PD, about the same effect as relaxing the carbon constraint from 3.0 to 3.7 w/m^2. While the optimal portfolios for the 3.0 PD and 3.7 PD sensitivity cases were identical, the optimal portfolios for 3.0 PD and LEI are different: in 3.0 PD nuclear is funded at the expense of CCS, and in LEI the opposite occurs.

Finally, these results show that simply throwing money at supply side R&D is not necessarily cost effective. Our results show that incremental return to investment drops sharply at the mid budget level, and spending at the high budget level is attractive only in the Low Bio case. The message here is that low carbon energy can only do so much and energy policy should include other measures such as demand side improvement (energy efficiency).

3.6. Future Work

This work analyzed the impact of technological change in low carbon energy supply technologies on consumption loss in the MESSAGE model and the impact of R&D investment into these technologies. It built on previous work with the GCAM model, which we discussed in depth in chapter 2. More generally, these chapters developed a methodology for analyzing R&D investment and technological change in integrated assessment models. Our methodology is designed with the principles of long term policy analysis in mind: it analyzes the impact of near term policy actions on long term outcomes, uses a large ensemble of scenarios, and is designed with flexibility in mind. Future work will focus on refining the methodology and expanding its application.

One important refinement of this methodology is to develop new metrics. This work considered only first-order effects of the TEaM parameters. While this approach showed that some parameters are clearly significant in their own right, there are probably important interactions between the parameters. For example, CCS may be especially valuable when paired with bioelectricity to produce a negative emission technology. These second-order and higher effects can be analyzed in a similar manner to the first order effects, provided that an appropriate regression model can be developed.

This methodology can also be applied to areas outside the supply side of the energy sector. For example, as discussed in section 3.2.2 there is growing interest in the connections between water, energy, and agriculture, particularly with respect to biomass feedstocks. Our methodology could be applied to this question by adding additional parameters to our elicitation data set. For example, elicitations with respect to the water intensity of biomass could improve the representation of biomass-induced land use changes, and in turn provide a clearer picture of the systemic effects of biomass.

CHAPTER 4

COMPARISON OF THE GCAM AND MESSAGE MODELS

4.1. Introduction

The previous two chapters examined how socioeconomic and energy system transformation pathways affect the value of technological change, and in turn R&D investment, in low carbon energy technologies. In both cases we saw that the relative importance of technologies and the overall value of technological change were sensitive to socioeconomic and technological assumptions. We also saw that the exercises of chapter 2 and 3 painted very different pictures of the potential role of each technology. For example, in chapter 2 nuclear was the dominant technology, while in chapter 3 nuclear was significant in only one case while bioliquids was the dominant technology.

Understanding the source of these differences is crucial for effective policy making. The variation could be the result of the different dimensions of our sensitivity analysis (socioeconomics vs energy system structure), or they could be the result of structural differences in model architecture (partial vs general equilibrium, recursive-dynamic vs intertemporal optimization, etc.). Distinguishing between these sources of variability is a vital step in understanding the implications of our results.

In this chapter we address this issue by considering inter-model variability between the MESSAGE and GCAM models. We will repeat the analysis from the previous chapters using input assumptions for both models that are, to the extent possible, identical. Our goal is to highlight the ways that the models can produce different results when given similar input scenarios in order to (1) suggest where there may be high value of information on model parameters and assumptions, and (2) place the results of the previous two chapters in context.

The balance of this chapter is organized as follows: In section 4.2 we discuss the issue of inter-model variability and some of the key differences between GCAM and MESSAGE. Section 4.3 we discuss the development of our harmonized input assumptions and section 4.4 discusses the results of our analysis. We conclude with a discussion of the policy implications of this work in section 4.5.

4.2. Background

As simplified representations of reality, models are by their very nature imperfect. This was perhaps best summarized by George Box, who is attributed with coining the aphorism *“all models are wrong but some are useful”* (Launer, Robert L., Wilkinson, Graham N., United States., Army Research Office.,Mathematics Division., 1979). It is also true that all models are different, even among models with similar goals. As the Energy Modeling Forum observed in 1977, *“Behind sharp differences on energy questions, there are often simple but fundamental differences in views about the nature of the problem.”* (Energy Modeling Forum 1977).

These two realities inevitably lead to variation in model outcomes. Rather than being a weakness, this phenomenon is a vital part of climate policy analysis. By analyzing the differences between model results, model inter-comparison studies provide valuable insight into both the climate change problem and the models themselves. This information can then be used to refine and improve both models and policy. This process is sometimes known as “deliberation with analysis” (NRC 2009).

Model intercomparison studies have a long and robust history. Beginning with their first report in 1977, the Stanford Energy Modeling forum has published 29 model intercomparison studies, with work ongoing on several others. Many other worldwide institutions have sponsored ongoing work in this area. Some recent examples include the EU sponsored Assessment of Climate Change Mitigation pathways and Evaluation of the Robustness of Mitigation Cost Estimates (AMPERE) (Kriegler et al. 2015b), and the Program on Integrated Assessment Modeling Development, Diagnostic and Inter-Comparisons (PIAMDDI) (Weyant 2010).

One focus of model intercomparison studies is to better understand the sources of inter-model variation. Kriegler et al. (2015a) categorized 11 IAMs into groups based on patterns of behavior in the models' response to carbon pricing. This exercise identified "diagnostic indicators" that can be used to classify models. Babiker et al. (2009) examined the implications of intertemporal versus recursive (myopic) solution approaches by modifying a single model to use either approach.

While these studies have provided important information, they focused more on modeling than on policy. Kriegler et al. (2015a) utilized technology scenarios designed for model diagnostics, rather than policy analysis, while Babiker et al. (2009) focused on the implications of the choice of solution dynamics. Neither of these studies sought to examine policy directly.

Other work has examined how more realistic technology inputs affect model outcomes. Bosetti et al. (2015) used the same TEaM data used in this work to characterize how uncertainty in technology outcomes affects model outcomes, but did not consider the impact of R&D on technology outcomes, nor did it analyze the MESSAGE model.

This work will build upon this knowledge base in order to examine how inter-model variation affects our previous work, in particular with respect to R&D investment portfolios. Instead of a broad analysis of model behavior under a wide range of conditions, we will examine model differences using the specific models and inputs of our study. We will also examine not only the differences in model behavior, but also the differences in the policy prescriptions that result.

4.2.1 GCAM vs MESSAGE

IAMs vary greatly in their architecture. Some of the major differences include the level of detail used to represent different systems, the theoretical framework under which they're designed, and the solution method. Models also differ in other ways, including time horizon, discount rate, and many others. In this section we will examine the differences most relevant to our analysis as they relate to GCAM and MESSAGE: theoretical framework, solution approach, and technological detail.

Models are generally designed under one of two theoretical frameworks: partial equilibrium or general equilibrium. Partial equilibrium models treat a portion of the economy in high detail while treating the balance of the economy exogenously. General equilibrium models trade depth for breath by modeling the entire economy at a lower level of detail.

GCAM is a partial equilibrium model; MESSAGE is a general equilibrium model. In GCAM the energy system is modeled in depth, but population and GDP are exogenous.

MESSAGE also models the energy system in detail, but also models (via MACRO) the broader economic impacts of the energy system.

Another key difference between models is the solution approach. Models can use either dynamic-recursive or intertemporal solution dynamics. Dynamic models solve each period in turn based on current conditions without regard to the future, although the decisions made in previous periods affect the choices available in future periods. Intertemporal models have foresight and solve all periods simultaneously.

The different solution approaches trade detail for speed. For example, intertemporal optimization facilitates analysis of capital investment dynamics and banking and borrowing of emissions, but have a much higher computational burden than myopic models. GCAM is dynamic recursive and MESSAGE is intertemporal.

A third major difference is the level of detail used in various sectors. The level of detail found in models varies widely depending on the research questions the model is designed to answer. Common areas of difference include the level of detail in the low carbon energy supply sector and the treatment of land use.

GCAM and MESSAGE differ in all three of these dimensions, however; the differences listed above are not exhaustive. The time horizon, discount rate, and method of treating climate impacts are all important considerations, although MESSAGE and GCAM do not differ substantially in these areas[5]. Moreover, the complexity of IAMs in general makes a comprehensive enumeration of differences impractical.

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5 GCAM and MESSAGE both use a 5% discount rate, a time horizon of 95-100 years, and model climate impacts using the MAGICC model to model (although they use different versions). See section 3.2.1 for a discussion of the MAGICC model.

4.3 Methods

Most of the data and methods used in this chapter have been previously introduced. We continue to use the TEaM data set that we have been using throughout (section 2.1.2). We calculate the CPL as described in section 2.2.3, and effect size and optimal portfolios as described in section 3.3. We adopt the population and GDP pathways of the GEA as described in section 3.2.2.

The main methodological difference in this chapter is that our sensitivity dimension is the models themselves, rather than input assumptions. To minimize the differences due to socioeconomic and energy system assumptions, this analysis requires, to the extent possible, identical input assumptions to both models. This strategy is implemented by adapting the GEA scenarios of chapter 3 to GCAM. The resulting GCAM outputs will then be comparable to the MESSAGE outputs of chapter 2.

4.3.1 Harmonizing the Input Assumptions

The socioeconomic assumptions and the carbon constraint must both be adapted to GCAM. In the case of the socioeconomic assumptions this requires mapping GEA scenario data from the MESSAGE regions into GCAM regions, then translating this information into GCAM input files. The carbon constraint was harmonized by tuning the emissions pathways in GCAM to achieve the desired forcing targets. We describe this process below.

4.3.1.1. Harmonizing Socioeconomic Assumptions

Harmonizing the population and GDP pathway is a 2 step process. First, the relevant data is mapped from its MESSAGE configuration into GCAM configuration. Next, the data is used to generate GCAM input files.

The first step in the harmonization process was to map the GEA population information into GCAM regions. Both GCAM and MESSAGE model socioeconomics and trade on a regional level, however there are slight differences between the composition of each region. Population and GDP data for each country was obtained from the publicly available GEA database (IIASA 2012). This data is supplied on the country level and is available in 10 year time steps from 2010 to 2100. This data was mapped into the appropriate GCAM regions to generate the GCAM population and GDP pathways. See Appendix for complete list of the MESSAGE and GCAM region for each country.

A socioeconomic pathway in GCAM is defined in terms of population, labor participation rate, and labor productivity as shown below:

$$GDP_t = POP_t * \varphi_t * \prod_t \frac{GDP_{Base}}{Pop_{Base} * \varphi_{Base}} (1 + \rho_t)^{n_t}$$

where t indexes the model period, φ is the labor force participation rate, ρ is the annual growth rate of labor productivity, and n is the number of years in the period.

We adopted the labor participation rates used in chapter 2 and set the base population and GDP according to the MESSAGE database. We use linear interpolation to convert the 10-year time steps in the MESSAGE population data into 5-year steps for GCAM.

4.3.1.2. Harmonizing the Forcing Constraint

In order to maintain consistency with the assumptions used in chapter 2 we used an exogenous emissions constraint to specify our forcing constraint. This is consistent with the Representative Concentration Pathway approach used in chapter 2.

Each of the RCP scenarios in GCAM has an associated emissions pathway. We calculated the 3.0 and 3.7 w/m^2 constraints by interpolating between the 2.6 and 4.5 w/m^2

constraints used in chapter 2. The interpolation was done using an iterative process, beginning with the 2.6 and 4.5 pathways. The resulting pathway was tested in GCAM and the actual results were then used as the starting point for a new interpolation. This process was repeated until the forcing constraint was within 1% of the desired target.

4.4. Results and Discussion

Table 14 summarizes the CPL and effect size data for the model comparison runs. CCS cost and solar have no CPL under any of the cases. The models show similar CPLs for bioelectricity efficiency under 3.0 PD and no CPL under 3.7 PD, however the negative effect size noted in section 3.4.1. is also present here. The models have different results for bioliquids efficiency as well, with MESSAGE returning an extremely low performance CPL and GCAM returning none at all. Bioliquids cost is also significant in MESSAGE but not GCAM, but the CPL is higher performance, around $0.85/GGE. The models also differ in their results for CCS efficiency, with GCAM showing an extremely low performance CPL of around 10% and MESSAGE showing none at all. Nuclear also shows radically different results for the models, with GCAM returning extremely low performance CPLs while MESSAGE CPLs are extremely high performance if they exist at all.

The optimal portfolios are summarized in

Table 15. The optimal portfolios for GCAM are identical for the 3.0 PD and 3.7 PD scenarios. The optimal portfolios for MESSAGE differ in only one place: the level of investment in bioelectricity at the low budget level. The biggest disagreement between the models is the investment in biofuels; MESSAGE calls for high investment across all budget levels while GCAM calls for low investment. The models also differ in the

investments in nuclear and bioelectricity, with GCAM favoring high investment in bioelectricity and MESSAGE investing in nuclear instead.

Table 14: CPL and Effect size for model comparison.

	CPL							
	BEE %	BEC $/kWh	BLE %	BLC $/GGE	CSC $/kW	CSE %	NUC $/kW	SOL $/kWh
3PD	47.53	0.02	23.20	0.84	-	-	-	-
GCAM 3pD	40.17	0.06	-	-	-	21.48	8077	-
3p7PD	-	-	23.20	0.86	-	-	857	-
GCAM 3p7PD	-	0.03	-	-	-	17.49	8007	-
	Effect Size							
	BEE	BEC	BLE	BLC	CSC	CSE	NUC	SOL
3PD	-0.01	-0.01	2.13	0.001	-	-	-	-
GCAM 3pD	0.02	0.03	-	-	-	0.02	0.46	-
3p7PD	-	-	1.86	0.002	-	-	0.01	-
GCAM 3p7PD	-	0.01	-	-	-	0.02	0.50	-

Table 15: Optimal Portfolios for model comparison.

		Technology				
	Budget	NUC	SOL	BE	BL	CCS
3.0 w/m^2	Low	Mid	High	Mid	High	Low
	Mid	High	High	Mid	High	Low
	High	High	High	Mid	High	Low
GCAM 3.0 w/m^2 GCAM 3.7 w/m^2	Low	Mid	High	High	Low	Low
	Mid	High	Low	High	Mid	Low
	High	High	Low	High	Mid	Low
3.7 w/m^2	Low	Mid	High	High	High	Low
	Mid	High	High	Mid	High	Low
	High	High	High	Mid	High	Low

The payoff of R&D is summarized in Figure 17 and Table 16. Between the low and mid budget levels, MESSAGE shows an increase in payoff of about 1% and GCAM shows a larger increase of 15-20%. Both models show no improvement in payoff between the mid and high budgets. For both models payoff is increasing in the stringency of the carbon constraint, but MESSAGE values R&D more highly than GCAM, with returns approximately 30-50% higher under MESSAGE than under GCAM. This is likely due to the slightly different metrics used: MESSAGE measures consumption loss across the entire economy, while GCAM measures only abatement cost without considering any ancillary losses in the larger economy.

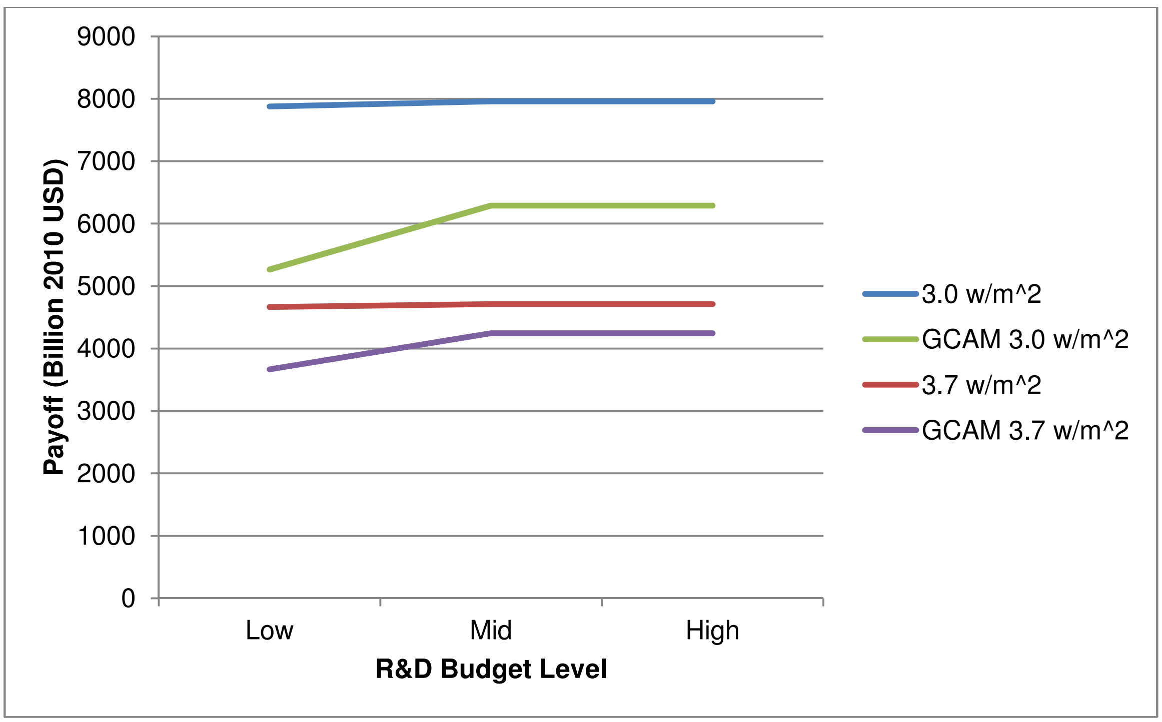

Figure 17: Payoff of R&D for model comparison exercise.

Table 16: Payoff of R&D for model comparison.

Budget Level	3.0 w/m^2	GCAM 3.0 w/m^2	3.7 w/m^2	GCAM 3.7 w/m^2
Low	7878	5266	4666	3667
Mid	7958	6288	4711	4246
High	7958	6288	4711	4246

In all cases returns to R&D are sharply decreasing. Incremental return to R&D is not attractive at all at the high budget level, and only GCAM shows an attractive incremental return at the mid budget level (Table 17 and Figure 18). As discussed in section 3.4.2, when incremental return is less than one investment at that budget level is not cost-effective.

Table 18 summarizes the optimal attractive portfolios. The optimal attractive portfolios are identical in GCAM and differ in only one case with MESSAGE. Both models call for low investment in CCS in all cases. The biggest disagreement occurs in solar, where MESSAGE calls for high investment and GCAM calls for low. One significant difference is that the largest attractive budget level is low for MESSAGE but mid for GCAM.

The differences in the optimal attractive portfolios is driven largely by the different attractive budget levels. At the low budget level the optimal portfolios are identical in three of the five technologies, while a comparison of the optimal attractive budget levels show agreement across models in only one case.

Table 17: Return and incremental return for model comparison.

Budget Level		3.0 PD	GCAM 3.0 w/m^2	3.7 PD	GCAM 3.7 w/m^2
Low	Return	180.24	134.27	81.95	61.71
	Incremental Return	180.24	134.27	81.95	61.71
Mid	Return	37.08	31.85	21.95	21.51
	Incremental Return	0.53	7.40	0.30	2.93
High	Return	37.08	31.85	21.95	21.51
	Incremental Return	0.00	0.00	0.00	0.00

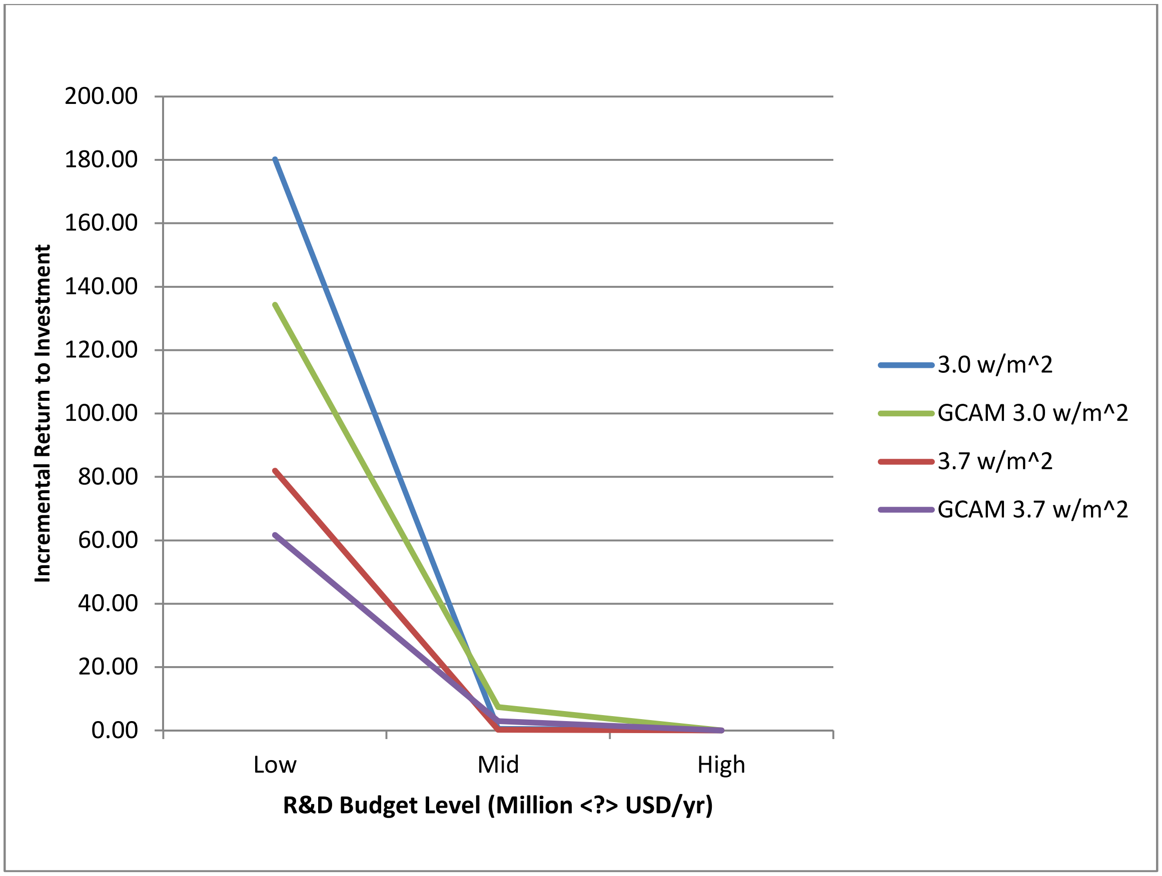

Figure 18: Incremental return to R&D for model comparison exercise.

Table 18:Optimal attractive portfolios for model comparison.

	Budget Level	NUC	SOL	BE	BL	CCS
3.0 w/m^2	Low	Mid	High	Mid	High	Low
GCAM 3.0 w/m^2	Mid	High	Low	High	Mid	Low
3.7 w/m^2	Low	Mid	High	High	High	Low
GCAM 3.7 w/m^2	Mid	High	Low	High	Mid	Low

4.5. Conclusions and Policy Implications

These results highlight several important policy considerations. Firstly, they indicate that R&D policy is robust within, but not across, models. They also highlight the value of a systems level approach to both valuing R&D and controlling policy costs. Finally, these results confirm the need for an improved understanding of bioenergy technologies.

These results highlight the impact of inter-model variability. While the policy prescriptions change little under our different carbon policies, they show significant disagreement across models. One of the most prominent differences is the difference in attractive budget levels between models. This difference leads in turn to markedly different optimal R&D portfolios.

Also interesting is that the optimal portfolios call for high investment in technologies with no CPLs. This occurs in MESSAGE in solar across all cases and bioelectricity in 3.7 PD. These phenomena indicate that our CPL methodology may not be capturing the entire value of a technology. This is consistent with interaction effects (which are not measured by our methodology) being present. This may also explain why CCS is not funded above the minimum level – it may be that CCS needs another technology – such as bioelectricity - to pair with in order to be effective. This argues for a systems-level approach and systems level metrics: R&D should be evaluated on its potential to impact *policy*, rather than technology costs.

The value of a systems-level approach is highlighted in a different way by the sharply diminishing returns to R&D investment seen in these results. Just as in chapter 3 we again see that returns to investment are sharply decreasing in R&D budgets. This implies that focusing on improvements in energy supply technologies may not be the best approach, and that other opportunities such as demand side improvements should be considered as alternative approaches for controlling policy costs.

These results also further reinforce the need to take a closer look at how models handle bioenergy. The relative impact of bioenergy technologies varies widely between the models, which results in significant differences in each model's optimal investment in bioenergy technologies. Understanding the drivers behind this behavior is an important first step in a larger evaluation of bioenergy technologies.

CHAPTER 5

CONTRIBUTIONS AND FUTURE WORK

5.1. Contributions

In this dissertation we developed a methodology for examining the impact of technological change in low carbon energy supply technologies on the cost of achieving climate targets and generating optimal R&D investment portfolios. We applied this methodology to two well-known IAMs; GCAM and MESSAGE, and performed sensitivity analysis across key dimensions of uncertainty: socioeconomic and energy system transformation pathways. We also performed a model intercomparison with GCAM and MESSAGE.

Chapter 2 developed our methodology for measuring the impact of technological change. We synthesized expert elicitation, importance sampling, and integrated assessment modeling to develop a method of modeling a large number of technological outcomes. We conducted a large ensemble of model runs using data developed as part of the TEaM project (the Elicitation Data Set (EDS)), then analyzed the output to characterize the impact of five low carbon energy technologies according to two metrics: (1) the minimum level of performance necessary to impact the cost of achieving CO2 emissions targets, and (2) the magnitude of the technology's impact. Among other things, we found that nuclear energy had the strongest impact on policy costs, while solar energy had a very small impact. This exercise also showed that the impact of technologies was sensitive to socioeconomic scenarios, especially high population, low GDP scenarios.

While chapter 2 provided insight into the *possible* impact of technologies, which allowed us to identify desirable outcomes, it provided little practical guidance for directing technological change in a desirable direction. In chapter 3 we addressed this issue by developing a method of optimizing R&D portfolios. Using importance sampling and probabilistic information about our technological outcomes, we developed a method of deriving optimal R&D portfolios. We again conducted a large ensemble of model runs. This ensemble again used the EDS, but used a different model, MESSAGE. Chapter 3's findings suggested that bioenergy technologies have a strong influence of policy costs, and that although the value of R&D is sensitive to the stringency of the carbon constraint, it has positive returns to investment even in a no-policy scenario. We also found that returns to investment in R&D are sharply decreasing, and that investing at the higher levels considered in our study was not cost effective.

Chapter 4 considered the question of inter-model variability. In this chapter we conducted model runs on both GCAM and MESSAGE using harmonized input assumptions and sensitivity cases in order to highlight the variability in outcomes resulting from the models themselves. We found that although the models yielded different outcomes with respect to technological impacts, that the overall policy prescriptions were similar. This chapter also reiterated the strong influence of bioenergy technologies and sharply decreasing returns to investment noted in chapter 3. Our results also indicated that the value of R&D is best measured in term of policy cost, rather than its direct impact on technology performance.

Aside from the specific findings discussed above this dissertation's main contribution was the development of our methodology. This methodology is a flexible framework that can be easily adapted to a wide range of models and research questions. The methods developed here can be applied to any integrated assessment model, and to any parameter of interest. Moreover, this method moves beyond the what-if analysis of prior studies by providing quantitative, rather than qualitative, measures of R&D's value.

5.2. Future Work

Future work will proceed along two fronts: refining our methodology and expanding the scope of the technologies and impacts considered. We will accomplish the former my developing new metrics for our analysis and the latter by expanding the elicitation database.

This work showed that our methodology can detect the influence of technological change on policy cost, but it also showed that the performance of a technology is often a poor measure of its value. This begs the question of what technological metrics, if any, would be a more effective measure. Some plausible candidates for such a metric are interactions between technologies that could represent synergistic combinations such as bioenergy with CCS, or the minimum cost technology from among a portfolio of electricity technologies.

We also intend to extend our consideration of technological change and impacts to new areas such as water and land use, two areas with strong potential to influence the supply of biomass. This could be accomplished by conducting elicitations about the development of less water-intensive crops, or more energy efficient technologies, or some other factor.

The overall goal of these efforts is to improve the quality if the inputs and assumptions that form the basis for integrated assessment modeling and policy analysis. The examples cited above are only a starting point. As this research progresses new avenues of inquiry will surely arise.

APPENDIX

COUNTRIES BY MESSAGE AND GCAM Reigon

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
Afghanistan	AFG	SAS	Southeast Asia
Albania	ALB	EEU	Eastern Europe
Algeria	DZA	MEA	Africa
American Samoa	ASM	PAS	USA
Andorra	AND	WEU	Western Europe
Angola	AGO	AFR	Africa
Antigua and Barbuda	ATG	LAC	Latin America
Argentina	ARG	LAC	Latin America
Armenia	ARM	FSU	Former Soviet Union
Australia	AUS	PAO	Austrailia_NZ
Austria	AUT	WEU	Western Europe
Azerbaijan	AZE	FSU	Former Soviet Union
Azores	PRT	WEU	Western Europe
Bahamas	BHS	LAC	Latin America
Bahrain	BHR	MEA	Middle East
Bangladesh	BGD	SAS	Southeast Asia
Barbados	BRB	LAC	Latin America
Belarus	BLR	FSU	Former Soviet Union
Belgium	BEL	WEU	Western Europe
Belize	BLZ	LAC	Latin America
Benin	BEN	AFR	Africa
Bermuda	BMU	LAC	Latin America
Bhutan	BTN	SAS	Southeast Asia
Bolivia	BOL	LAC	Latin America
Bosnia and Herzegovina	BIH	EEU	Eastern Europe
Botswana	BWA	AFR	Africa
Brazil	BRA	LAC	Latin America
British Indian Ocean Territory	IOT	AFR	Africa
Brunei Darussalam	BRN	PAS	Southeast Asia
Bulgaria	BGR	EEU	Eastern Europe
Burkina Faso	BFA	AFR	Africa
Burundi	BDI	AFR	Africa
Cambodia	KHM	CPA	Southeast Asia
Cameroon	CMR	AFR	Africa
Canada	CAN	NAM	Canada

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
Canary Islands	ESP	WEU	Western Europe
Cape Verde	CPV	AFR	Africa
Central African Republic	CAF	AFR	Africa
Chad	TCD	AFR	Africa
Channel Islands	0	WEU	Western Europe
Chile	CHL	LAC	Latin America
China (incl. Hong Kong)	CHN	CPA	China
Colombia	COL	LAC	Latin America
Comoros	COM	AFR	Africa
Congo	COD	AFR	Africa
Costa Rica	CRI	LAC	Latin America
Cote d'Ivoire	CIV	AFR	Africa
Croatia	HRV	EEU	Eastern Europe
Cuba	CUB	LAC	Latin America
Cyprus	CYP	WEU	Western Europe
Czech Republic	CZE	EEU	Eastern Europe
Denmark	DNK	WEU	Western Europe
Djibouti	DJI	AFR	Africa
Dominica	DMA	LAC	Latin America
Dominican Republic	DOM	LAC	Latin America
Ecuador	ECU	LAC	Latin America
Egypt (Arab Republic)	EGY	MEA	Africa
El Salvador	SLV	LAC	Latin America
Equatorial Guinea	GNQ	AFR	Africa
Eritrea	ERI	AFR	Africa
Estonia	EST	EEU	Former Soviet Union
Ethiopia	ETH	AFR	Africa
Faeroe Islands	FRO	WEU	Western Europe
Fiji	FJI	PAS	Southeast Asia
Finland	FIN	WEU	Western Europe
France	FRA	WEU	Western Europe
French Guyana	GUF	LAC	Latin America
French Polynesia	PYF	PAS	Southeast Asia
Gabon	GAB	AFR	Africa
Gambia	GMB	AFR	Africa
Georgia	GEO	FSU	Former Soviet Union
Germany	DEU	WEU	Western Europe
Ghana	GHA	AFR	Africa
Gibraltar	GIB	WEU	Western Europe
Gilbert-Kiribati	KIR	PAS	Southeast Asia
Greece	GRC	WEU	Western Europe

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
Greenland	GRL	WEU	Western Europe
Grenada	GRD	LAC	Latin America
Guadeloupe	GLP	LAC	Latin America
Guam	GUM	NAM	USA
Guatemala	GTM	LAC	Latin America
Guinea	GIN	AFR	Africa
Guinea-Bissau	GNB	AFR	Africa
Guyana	GUY	LAC	Latin America
Haiti	HTI	LAC	Latin America
Honduras	HND	LAC	Latin America
Hungary	HUN	EEU	Eastern Europe
Iceland	ISL	WEU	Western Europe
India	IND	SAS	India
Indonesia	IDN	PAS	Southeast Asia
Iran (Islamic Republic)	IRN	MEA	Middle East
Iraq	IRQ	MEA	Middle East
Ireland	IRL	WEU	Western Europe
Isle of Man	IMN	WEU	Western Europe
Israel	ISR	MEA	Middle East
Italy	ITA	WEU	Western Europe
Jamaica	JAM	LAC	Latin America
Japan	JPN	PAO	Japan
Jordan	JOR	MEA	Middle East
Kazakhstan	KAZ	FSU	Former Soviet Union
Kenya	KEN	AFR	Africa
Korea (DPR)	PRK	CPA	China
Kuwait	KWT	MEA	Middle East
Kyrgyzstan	KGZ	FSU	Former Soviet Union
Laos (PDR)	LAO	CPA	Southeast Asia
Latvia	LVA	EEU	Former Soviet Union
Lebanon	LBN	MEA	Middle East
Lesotho	LSO	AFR	Africa
Liberia	LBR	AFR	Africa
Libya/SPLAJ	LBY	MEA	Africa
Liechtenstein	LIE	WEU	Western Europe
Lithuania	LTU	EEU	Former Soviet Union
Luxembourg	LUX	WEU	Western Europe
Madagascar	MDG	AFR	Africa
Madeira	PRT	WEU	Western Europe

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
Malawi	MWI	AFR	Africa
Malaysia	MYS	PAS	Southeast Asia
Maldives	MDV	SAS	Southeast Asia
Mali	MLI	AFR	Africa
Malta	MLT	WEU	Western Europe
Martinique	MTQ	LAC	Latin America
Mauritania	MRT	AFR	Africa
Mauritius	MUS	AFR	Africa
Mexico	MEX	LAC	Latin America
Monaco	MCO	WEU	Western Europe
Mongolia	MNG	CPA	China
Morocco	MAR	MEA	Africa
Mozambique	MOZ	AFR	Africa
Myanmar	MMR	PAS	Southeast Asia
Namibia	NAM	AFR	Africa
Nepal	NPL	SAS	Southeast Asia
Netherlands	NLD	WEU	Western Europe
Netherlands Antilles	ANT	LAC	Latin America
New Caledonia	NCL	PAS	Southeast Asia
New Guinea	PNG	PAS	Southeast Asia
New Zealand	NZL	PAO	Austrailia_NZ
Nicaragua	NIC	LAC	Latin America
Niger	NER	AFR	Africa
Nigeria	NGA	AFR	Africa
Norway	NOR	WEU	Western Europe
Oman	OMN	MEA	Middle East
Pakistan	PAK	SAS	Southeast Asia
Panama	PAN	LAC	Latin America
Papua	PNG	PAS	Southeast Asia
Paraguay	PRY	LAC	Latin America
Peru	PER	LAC	Latin America
Philippines	PHL	PAS	Southeast Asia
Poland	POL	EEU	Eastern Europe
Portugal	PRT	WEU	Western Europe
Puerto Rico	PRI	NAM	USA
Qatar	QAT	MEA	Middle East
Republic of Korea	KOR	PAS	South Korea
Republic of Moldova	MDA	FSU	Former Soviet Union
Reunion	REU	AFR	Africa
Romania	ROU	EEU	Eastern Europe
Russian Federation	RUS	FSU	Former Soviet Union

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
Rwanda	RWA	AFR	Africa
Saint Helena	SHN	AFR	Africa
Saint Kitts and Nevis	KNA	LAC	Latin America
Saint Vincent and the Grenadines	VCT	LAC	Latin America
Santa Lucia	LCA	LAC	Latin America
Sao Tome and Principe	STP	AFR	Africa
Saudi Arabia	SAU	MEA	Middle East
Senegal	SEN	AFR	Africa
Seychelles	SYC	AFR	Africa
Sierra Leone	SLE	AFR	Africa
Singapore	SGP	PAS	Southeast Asia
Slovak Republic	SVK	EEU	Eastern Europe
Slovenia	SVN	EEU	Eastern Europe
Solomon Islands	SLB	PAS	Southeast Asia
Somalia	SOM	AFR	Africa
South Africa	ZAF	AFR	Africa
Spain	ESP	WEU	Western Europe
Sri Lanka	LKA	SAS	Southeast Asia
Sudan	SDN	MEA	Africa
Suriname	SUR	LAC	Latin America
Swaziland	SWZ	AFR	Africa
Sweden	SWE	WEU	Western Europe
Switzerland	CHE	WEU	Western Europe
Syria (Arab Republic)	SYR	MEA	Middle East
Taiwan (China)	TWN	PAS	China
Tajikistan	TJK	FSU	Former Soviet Union
Tanzania	TZA	AFR	Africa
Thailand	THA	PAS	Southeast Asia
The former Yugoslav Rep. of Macedonia	MKD	EEU	Eastern Europe
Togo	TGO	AFR	Africa
Tonga	TON	PAS	Southeast Asia
Trinidad and Tobago	TTO	LAC	Latin America
Tunisia	TUN	MEA	Africa
Turkey	TUR	WEU	Western Europe
Turkmenistan	TKM	FSU	Former Soviet Union
Uganda	UGA	AFR	Africa
Ukraine	UKR	FSU	Former Soviet Union
United Arab Emirates	ARE	MEA	Middle East
United Kingdom	GBR	WEU	Western Europe

Country	ISO ALPHA-3	MESSAGE Region	GCAM Region
United States of America	USA	NAM	USA
Uruguay	URY	LAC	Latin America
Uzbekistan	UZB	FSU	Former Soviet Union
Vanuatu	VUT	PAS	Southeast Asia
Venezuela)	VEN	LAC	Latin America
Viet Nam	VNM	CPA	China
Virgin Islands	VIR	NAM	USA
Western Samoa	WSM	PAS	Southeast Asia
Yemen	YEM	MEA	Middle East
Yugoslavia	0	EEU	Eastern Europe
Zaire	COD	AFR	Africa
Zambia	ZMB	AFR	Africa
Zimbabwe	ZWE	AFR	Africa

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