Assessing Early Investments in Low Carbon Technologies under Uncertainty: The Case of Carbon Capture and Storage

by

Eleanor Charlotte Ereira

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Signature of Author………………………………………………………………………………
Technology and Policy Program, Engineering Systems Division
May 7, 2010

Certified by………………………………………………………………………………………
Howard J. Herzog
Senior Research Engineer, MIT Energy Initiative
Thesis Supervisor

Certified by………………………………………………………………………………………
Mort D. Webster
Assistant Professor, Engineering Systems Division
Thesis Supervisor

Accepted by……………………………………………………………………………………...
Dava J. Newman
Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

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Abstract

Climate change is a threat that could be mitigated by introducing new energy technologies into the electricity market that emit fewer greenhouse gas (GHG) emissions. We face many uncertainties that would affect the demand for each of these technologies in the future. The costs of these technologies decrease due to learning-by-doing as their capacity is built out. Given that we face uncertainties over future energy demands for particular technologies, and that costs reduce with experience, an important question that arises is whether policy makers should encourage early investments in technologies before they are economically competitive, so that they could be available in the future at lower cost should they be needed. If society benefits from early investments when future demands are uncertain, then there is an option value to investing today. This question of whether option values exist is investigated by focusing on Coal-fired Power Plants with Carbon Capture and Storage (CCS) as a case study of a new high-cost energy technology that has not yet been deployed at commercial scale.

A decision analytic framework is applied to the MIT Emissions Prediction Policy Analysis (EPPA) model, a computable general equilibrium model that captures the feedback effects across different sectors of the economy, and measures the costs of meeting emissions targets. Three uncertainties are considered in constructing a decision framework: the future stringency of the US GHG emissions policy, the size of the US gas resource, and the cost of electricity from Coal with CCS. The decision modeled is whether to begin an annual investment schedule in Coal with CCS technology for 35 years. Each scenario in the decision framework is modeled in EPPA, and the output measure of welfare is used to compare the welfare loss to society of meeting the emissions target for each case. The decision framework is used to find which choice today, whether to invest in CCS or not, gives the smallest welfare cost and is therefore optimal for society. Sensitivity analysis on the probabilities of the three uncertainties is carried out to determine the conditions under which CCS investment is beneficial, and when it is not.

The study finds that there are conditions, specified by ranges in probabilities for the uncertainties, where early investment in CCS does benefit society. The results of the decision analysis demonstrate that the benefits of CCS investment are realized in the latter part of the century, and so the resulting optimal decision depends on the choice of discount rate. The higher the rate, the smaller the benefit from investment until a threshold is reached where choosing to invest becomes the more costly decision. The decision of whether to invest is more sensitive to some uncertainties investigated than others. Specifically, the size of the US gas resource has the least impact, whereas the stringency of the future US GHG emissions policy has the greatest impact.

This thesis presents a new framework for considering investments in energy technologies before they are economically competitive. If we can make educated assumptions as to the real probabilities we face, then extending this framework to technologies beyond CCS and expanding the decision analysis, would allow policymakers to induce investment in energy technologies that would enable us to meet our emissions targets at the lowest cost possible to society.

Thesis Supervisors:

Howard J. Herzog, Senior Research Engineer, MIT Energy Initiative
Mort D. Webster, Assistant Professor, Engineering Systems Division

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1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC, 2009) states that the warming of the climate system is unequivocal, and that this is very likely due to increases in anthropogenic greenhouse gas (GHG) concentrations. Approximately 40% of US greenhouse gas emissions are from generating electricity, and therefore any solution to the problem of climate change must address emissions from the power sector (EIA, 2009d). Currently, coal provides approximately half the electricity in the US and produces the most carbon emissions on a per kilowatt basis (EIA, 2008). Therefore reducing emissions in the power sector will require replacing current coal-fired power plants with lower carbon emitting technologies such as gas, nuclear power, coal or gas with carbon capture and storage (CCS), and/or renewables such as biomass, wind or solar.

However, each of these potential low-carbon technologies has significant uncertainties in its future cost, availability, and performance, as well as potential interactions with other technologies in the electric power system. Given the uncertainties, it is difficult to know today what is the best energy mix that will meet our long run carbon reduction objectives.

One major uncertainty concerns the emissions policy that will be in place in the future. Today there is no national regulation in the US of GHG emissions. It is possible that legislation could be enacted in the coming years because addressing climate change has recently become a higher priority on the political agenda in Congress and the White House. This possibility has been demonstrated by the passage of the American Clean Energy and Security Act in the House of Representatives in June 2009, signifying that although no bill has passed in the Senate so far, it is plausible that regulations could be enacted in the future. However, even if legislation were passed today, such as a cap and trade system, it is unlikely that any policy enacted now will remain unchanged in the long-term.

For example, legislation such as a cap and trade bill could specify annual emissions limits for the next 50 or 100 years, but new information within that time frame may lead us to want to change the path of the emissions limits. This could be the result of new scientific evidence on the severity of climate change or shifting priorities in international relations. If the emissions policy were adjusted to reflect this new information, then the associated price of carbon would be affected. This would change the demand for cleaner energy sources, which in turn would affect the energy mix.

Another factor that could affect which low-carbon energy technology plays a large role is the abundance of the fuel resource for that technology. Currently in the US, unconventional natural gas is receiving heightened attention due to new resource discoveries and technological improvements that could enable us to extract shale gas, tight gas and coalbed methane at competitive cost. Making full use of this increased resource would result in lower prices of electricity generated from gas, pushing out other technologies from the mix. It is unclear today, however, to what extent this resource will be tapped, and therefore we do not know what fraction of electricity will be demanded from gas plants.

A further uncertainty we face is the cost of advanced technologies that could replace current generation. Even if a stringent emissions policy is applied, there are many potential technologies that have low GHG emissions, and we do not know which will end up being the lowest cost. There is significant uncertainty surrounding the future costs of technologies that are not yet commercialized at scale, or are still undergoing technological development such as CCS or solar photovoltaic technologies. Again, because of this uncertainty, we do not know what energy mix will be needed to reach our long-term emissions targets.

Given these uncertainties, we cannot accurately predict the energy technology mix of the future that would result under any GHG policy. This presents difficulties for policy makers today deciding on whether they should enact policies to encourage and support investments in technologies that are currently prohibitively expensive that may be demanded later. For example, coal-fired generation with CCS technology today is uncompetitive due to its cost and the fact it has not been demonstrated commercially at scale. Even if CO_2 emissions are limited through a program such as cap and trade, unless the price of carbon is high enough, approximately 65$/ton CO_2, CCS will never be competitive and will not be deployed at large scale (Hamilton, 2009).

If the carbon price does become high enough for CCS to begin to penetrate the electricity market, the costs will then decrease through learning-by-doing, as we become experienced with the technology, pass regulations ensuring safe long-term CO_2 storage and build out the associated infrastructure. This will in turn leads to further market penetration and more cost reductions. It takes time for costs to reduce from a first-of-a-kind generation to an n^{th}-of-a-kind, as technological readiness is achieved. This kind of cost reduction is known as 'demand-pull' innovation (Arrow, 1962).

Given that costs decrease with experience, and that we face substantial uncertainty over future demands for energy technologies, this motivates the question of whether there could be benefits to society from early investments in high-cost, unproven technologies to accelerate the learning-by-doing process, so that we have the option of using them in the future at lower costs should demand increase unexpectedly. Decreasing costs in this way is called 'technology-push' innovation, forcing the learning-by-doing before a market exists for the technology. Combining a technology-push strategy such as an early investment, with a market-pull through a cap and trade system, would mean society has the option of using this low emitting technology at a reduced cost (n^{th}-of-a-kind rather than first-of-a-kind) in the future if the carbon price gets high enough for it to be competitive since the learning will have already occurred. Since there is significant uncertainty in the future that would affect the level of demand-pull for a technology such as CCS, and if we believe that demand could increase beyond what we envision today due to these uncertainties, then it may be worth investing in CCS today. Early investment could provide an option value as society would benefit from having the option to build CCS at lower costs should this unexpected demand increase exist.

The definition of an option value is when a rational agent sees value in paying a sum of money today for the right to use an asset or service in the future (Smith, 1983). With regard to CCS investments, the uncertainty we face is whether demand for the technology will increase rapidly, forcing us to build the technology quickly. If demand for CCS does increase quickly, we will have preferred that we had made early investments and started the learning-by-doing process to drive down costs. If demand for CCS does not increase, we will have preferred that we had not paid up front to force learning, as it will have been unnecessary. Most option analyses would provide a mid-way alternative where we would pay for an action that would give us the option of learning and building out more at lower cost if we so needed. This thesis only investigates whether we should invest today or not, examining the extremes of the alternative actions. Therefore, this thesis presents a somewhat unconventional interpretation of the term option value. However, investing in CCS would involve paying an upfront cost today so that we have the ability to build out CCS cheaply in the future if we need to. Therefore, for this particular analysis, the view that investing in CCS could provide an option value holds with the above definition, and if society were to benefit from early investments, then there is indeed a positive option value.

This thesis explores the conditions under which this option value could exist, where early investment would allow the US to meet emissions targets in the future at a lower cost to society than without investment, which would therefore improve welfare and benefit society. The purpose of this study is provide a new framework for assessing how government should decide whether to encourage investments in energy technologies given uncertainty and learning-by-doing, by taking CCS as a case study of a new, expensive energy technology.

CCS is an interesting and pertinent case study for this issue as the climate legislation recently passed in the House of Representatives, and the counterpart proposal in the Senate, contain substantial incentives for CCS, and so policy makers are indeed faced with the decision today of whether to support the technology. HR2454, the American Clean Energy and Security Act, allocates a percentage of the allowances created under the cap and trade program to CCS projects, which is direct financial support as the allowances have value since the cap creates a market for carbon. 1.175% is allocated from 2014 to 2017, 4.75% from 2018 to 2019, and 5% from 2020 to 2050. Further, a bonus allowance of $90/ton CO_2 captured is also provided for the first 6GW from CCS units with a capture rate for 85% or higher. After the first 6 GW further governmental support is provided through a reverse auction (Waxman & Markey, 2009). Studies of the total value of incentives for CCS estimate the amount to be in the range of $240B from 2012 through to 2050 (Pew Center for Global Climate Change, 2009). This is a significant sum of money, and therefore efforts to better understand the true value of investing large sums in

CCS, and whether this is beneficial to society given that the future is uncertain, are important for informing the current debate.

In addition to a direct subsidy, policy makers can also use other tools to encourage private investment in CCS projects. The Office of Fossil Energy at the US Department of Energy is continuing the FutureGen project to build an integrated gasification combined cycle power plant with CCS in Mattoon, Illinois, in partnership with the FutureGen Industrial Alliance Inc, an industrial consortium of twenty companies that will contribute $20 to $30 million each over a four to six year period (US Department of Energy, 2009).

Since considerably sized CCS investments are already occurring to a certain extent in the USA, and potential legislation could increase this considerably, analysis to investigate whether this is the right action to take and whether it could benefit society as a whole is an important effort.

There are many studies intended to aid policymakers that prescribe roadmaps and measures for reaching certain technology mixes that would deliver emissions cuts, such as Socolow and Pacala's (2004) Wedge analysis and the EPRI Prism analysis (Douglas, 2007). These reports are deterministic in nature and do not take into account the reality that the future is uncertain, and therefore make no allowance for us to adapt as we learn more about the way in which we wish to act in response to new information on climate change. Because these analyses are deterministic, they do not capture any potential option values of policies that may exist, since under perfect information, actions that give us options in the future are wasteful. These reports are therefore missing an important element in their analysis intended for aiding policy decisions.

There are also multiple reports on how endogenous technical change in models such as R&D and learning-by-doing can effect the diffusion of technologies and the associated costs, such as Kohler at al. (2006). This thesis builds on the work of these reports by combining modeling innovation through cost reduction with the issue of uncertainty and option values.

In order to more directly assess the value of early investment in CCS today than previous studies have, this thesis asks the following research question:

Given the uncertainty in the future energy mix, and the existence of learning-by-doing, under what conditions is there an option value to society if we invest in CCS today so that we could use it in the future at a lower cost?

This question is explored within a decision analysis framework, intended to inform policymakers who are considering whether to either directly fund or promote programs that encourage investment today in energy technologies, such as CCS. The issue is investigated using the MIT Emissions Prediction Policy Analysis (EPPA) model, a CGE model that reports the impact of climate policies on the economy (Paltsev et al., 2005a). The thesis examines how investment in CCS before it is economically viable affects the costs to society of meeting an emissions path when faced with uncertainties. One uncertainty that is modeled is the stringency of the emissions path, which could get either stricter or less stringent than anticipated, changing the demand for clean energy technologies in each case. Two additional uncertainties, the size of the natural gas resource in the US and the long-run cost of CCS, are also investigated to explore the conditions where there is an option value to investing in CCS. The costs to society in EPPA are a measure of welfare. The welfare output for the different scenarios examined are analyzed in a decision model, where the decision is whether or not to invest in CCS today. The decision model is used to find the decision today that maximizes welfare over the whole time period examined.

This thesis is solely concerned with whether financial support to CCS can be beneficial to the US as a whole and does not address the issue of who should make these investments, and whether the funding should come directly from government, or whether policy makers should encourage private investment through mechanisms such as public/private partnerships, standards or R&D tax credits. The model used for this analysis, as explained in section 3.1.3, does not distinguish between the public and private sectors as there is only one representative agent, and therefore the question of who should invest in CCS is beyond the scope of this thesis.

By examining CCS as a case study, this thesis provides a means for analyzing whether investments in CCS, a relevant and real possibility, are beneficial or not to society. Further, a similar framework can be used to consider making investments across the spectrum of all low

GHG emitting energy technologies. In this way, the decision framework presented could be extended to determine an optimal investment portfolio across technologies that maximize social welfare while meeting our broader GHG emissions policies.

Chapter 2 provides an overview of the existing literature on the issues of forecasting future energy technology mixes, modeling endogenous technical change such as learning-by-doing through financial support, and decision under uncertainty. The chapter will also discuss why CCS is an interesting and relevant energy technology to examine as a case study in answering the question of whether early investment adds an option value to society. Chapter 3 explains the methodology behind the approach, discussing the EPPA model and the decision analysis. Chapter 4 presents the results, and chapter 5 discusses interpretation of the results, and how the decision framework could be extended beyond considering only CCS investments.

2 Background

This chapter outlines the published literature relevant to the issue of whether making early investments in CCS under uncertainty given that learning-by-doing exists, can benefit US society as a whole. The chapter also describes how this thesis builds on the existing studies.

This section reviews published studies concerning energy technology deployment forecasts, uncertainty in climate policy, financial support of energy technologies, and learning and modeling endogenous technical change. A discussion on why it is appropriate to explore investment for CCS technology in particular in examining how investments might lower the cost of meeting emissions targets given an uncertain future is also presented.

2.1 Energy technology deployment forecasts

2.1.1 Modeling future technology mixes

There are many reports that are intended to inform policy makers about what energy sources should be used to avoid serious irreversible harms from climate change. One such report is Socolow and Pacala's (2004) wedge analysis. Their study gives an estimate of business as usual (BAU) emissions, and an emissions reduction target of 7GtC/year over the next 50 years. The authors suggest different technologies that we could use to fill the gap between BAU emissions and the target, thus lowering our emissions by 7GtC every year. This is a useful exercise in demonstrating the different mitigation options and showing that there is likely no one technology that we can expand enough to fill the gap alone. However, extending this to policymaking becomes difficult, as the authors have assumed a deterministic scenario in which we know our emissions targets, and what we are able to achieve with each technology.

Another widely cited study with deterministically prescribed technology mixes is the Electric Power Research Institute (EPRI) Prism Analysis (Douglas, 2007). Socolow and Pacala pick an equal amount of CO_2 reductions from each of the technologies used to fill the emissions gap, whereas the EPRI study projections are based on capacities that studies have suggested could be achieved from each technology with aggressive climate policies. Both of these studies do not take into account the fact that the contributions from each wedge or prism section are not independent of each other, and therefore do not necessarily add to the given total as reported as the important feedback effects that would occur in reality are not captured.

Several reports focus specifically on the policies we would need to deploy CCS within the energy technology mix. For example, the International Energy Agency (IEA) published a set of roadmaps in 2009 envisioned to advise policy makers on the necessary steps on how to build out different technologies to a specified capacity. A CCS Roadmap was published as part of the study and describes the necessary procedures to ensure the financing, regulatory and technological hurdles are overcome (2009). The suite of roadmaps recommend policies to reach certain capacities specified in the results of a 50% reduction of 2005 CO_2 emissions by 2050 given by the MARKAL (MARKet ALlocation) model, specifically designated as the Energy Technology Perspectives (ETP) BLUE scenario. Although several sensitivities are examined, the study assumes that the emissions target is fixed and prescribes actions accordingly, also not allowing for the reality that our emissions paths and targets are uncertain.

Bistline and Rai (2010) explore different ways in which CCS could be built out in the future by performing sensitivities on the EPRI Prism Analysis study with different learning rates. Similarly to the EPRI study, the work is based on deterministically found targets for capacity that do not take emissions policy uncertainties or interactions of technologies and feedbacks into account (although the authors acknowledge this latter issue and explicitly state that representation of the assumptions in a CGE model is required to examine the feedback effects and results when demand for CCS changes, which is part of the analysis carried out in this study).

Even if we accepted that the prescribed technology build-out recommendations would result in the specified emissions decrease, these reports give insight into only one scenario, when the emissions reduction target in the future is known today. In reality our future emissions path is uncertain. Papers of this kind are aiming for a stationary target, a specified emissions reduction based on today's knowledge and capabilities, when in reality we are facing a moving target. This moving target is the improved emissions path, which is revised over time as we learn about the severity of climate change and relative energy technology capacities and costs. Therefore it is conceivable that following deterministic advice of this kind would lead us to miss our goal of avoiding harms from climate change at the lowest cost possible.

Other studies treat the uncertainty in a limited fashion, either by providing a few alternative scenarios with different assumptions, or by comparing the results of an analysis across several models. An example of a study that provides alternative scenarios is the Annual Energy Outlook by the US Energy Information Administration (EIA, 2009a). The Annual Energy Outlook publishes results based on the results of the National Energy Modeling System (NEMS), a model that projects US energy markets for a 20-year horizon. By balancing supply and demand of all the energy producing and consuming sectors aggregated into modules, NEMS gives projections of what may happen given the assumptions made, such as high or low growth, and different climate policies. Although the AEO reports do explore the energy mix that could result from several different assumptions about the future, the number of scenarios explored is small (four or five) in any given report. Further, the reports only include policies that have already been passed in congress. This provides only limited information because it does not account for possible future policy changes.

An example of a multi-model comparison is the US Climate Change Science Program (CCSP) Synthesis and Assessment Product 2.1a (Clarke et al., 2007). This report compares the global path of emissions that would be required to achieve a range of radiative forcing stabilization targets from three different integrated assessment models: the MIT Integrated Global Systems Model (IGSM) (Sokolov et al., 2005), Stanford's Model for Evaluating the Regional and Global Effects (MERGE) (Manne & Richels, 2005), and MiniCAM of Pacific Northwest National Lab (Brenkert et al., 2003). The comparison across the models' results is performed for several stabilization scenarios, but does not include a framework for actions given that we don't know future stabilization levels, and explicitly states that the focus of the study is on scenarios and not uncertainty analysis. The IPCC's assessments, the latest being the Fourth Assessment Report (2009), give an aggregation of many different models' results when certain specific assumptions are made. Like the EIA reports, this is an example where only a small number of scenarios are examined, again providing only limited insight into future uncertainties. Another similarity with the EIA reports is that only existing policies are modeled, and therefore the report does not account for potential policy changes.

All of these reports – EIA, CCSP, IPCC – model uncertainty by using different scenarios to represent possible futures. While this is a useful first step in communicating to policymakers the range of possible outcomes, it has limitations. Specifically, the results under a given scenario for a particular model convey what can or what should be done if that set of assumptions were true, and if we knew it was true with no uncertainty. They do not necessarily give insight into how to choose between policies under uncertainty.

In this thesis, I explicitly explore choices in the context of future uncertainties in the energy mix, by applying a decision analytic framework. Representing decisions under uncertainty will allow us to estimate the value of various policy options. This will provide useful insights to decision makers because, as past experiences have shown us, our future climate policies and scientific knowledge are indeed uncertain.

2.1.2 US future climate policy is uncertain

The future US climate policy is uncertain both because of potential changes in the political agenda, and because of the unpredictable progress of scientific evidence supporting climate change.

Although arguably the US stance on climate legislation has been consistent for the past two decades in the sense that regulations for CO_2 have never been enacted, discussions and support for regulating emissions have been on the rise in Congress. The U.S. could be closer than ever to passing legislation on CO_2 emissions, since the House passed HR2454, the first time comprehensive climate legislation has ever been passed in either chamber. However, it is still unclear if legislation will be passed in the Senate, and what the final version of a climate bill will look like. Even if a bill is passed, support for climate legislation is a very controversial issue, with powerful politicians and lobbies on either side of the debate (Cowan & O'Callaghan, 2009).

President Obama supports the passage of climate legislation. However, presidential terms are four years in the US, and with only a two term maximum in office, Obama will be replaced and it is unclear whether future administrations will continue his support for CO_2 emissions regulations. Even if legislation is passed in the near future, should the tide change towards electing officials with differing views on political action to limit GHG emissions several years in the future, these regulations could be changed to reflect this. Given the uncertainty over the political will of future administrations to regulate carbon, the emissions policies of the future are also uncertain, even if passed in the near-term.

As well as changing political agendas, another factor that makes the US future emissions policy uncertain is developments in the science of climate change. New scientific discoveries can lead to new policies being passed. However, we do not know if or when these discoveries will occur, or what they will tell us about the severity of climate change. Therefore, the policies that could result from these scientific developments are also unknown.

An example where scientific developments have resulted in changing policies in the environmental science realm is the banning of chlorofluorocarbons (CFCs) through the Montreal Protocol, when scientists discovered stratospheric ozone depletion as a result of CFC use. Oye and Maxwell (2005) provide an account of the increasing scientific evidence that finally led to regulation. They write that an article in Nature in 1974 (Molina & Rowland, 1974) followed by a National Academies of Science report (1979) drew attention to the potential capacity of CFCs to cause depletion to the ozone layer, and the damages that could result in terms of skin cancer and crop yield. No meaningful regulations were passed although pressure to act had started to build when, in 1985, an article was published on a study that had observed the ozone hole over Antarctica (Farman et al., 1985). This scientific evidence was enough to remove ambiguity over whether the concern was legitimate, and after international negotiations the Montreal Protocol was signed later that year.

Although there were other factors at play that allowed regulations to be passed, such as regulatory capture and the availability of alternatives to CFCs, the development of the scientific evidence was the cornerstone for the evolution of the policies on CFC use. Since we do not know how the scientific evidence on climate change will progress, there is uncertainty over the future climate policies the US could enact as a result.

As political priorities and the progression of scientific evidence on climate change are unknowable, uncertainties in future climate policies are a reality. Given this, analysis on valuing policy alternatives should account for this uncertainty, as we may place higher value on decisions that give us options to use technologies in the future, since we do not now what our demands will be.

2.2 Decision under uncertainty in climate policy

Within the broader study of uncertainty, there are two distinct types of analyses. One approach estimates the likelihoods of certain events occurring, and assigns probabilities to these uncertainties. These studies are often carried out using Monte Carlo analysis, such as New and Hulme (2000), and Kelly and Kolstad (1999). The second analysis approach addresses how to make decisions in the presence of uncertainty, and it is this latter concept that is applied in this thesis.

Weisbrod (1964) was the first economist to write that there is an option value in situations where demand is uncertain and consumers are willing to pay for the option of using a commodity in the future. Based on this assumption, by recognizing the uncertainty in future CCS demand, concurrently with modeling learning-by-doing, this thesis explores the value of investment because it provides the option of building CCS at a lower cost in the future.

Several reports have discussed the issues of irreversibility, and how this impacts decision under uncertainty. This is pertinent to climate change as many scientists believe in a ‘tipping-point’ in emissions, beyond which the global climate system will transform irreversibly. Arrow and Fisher

(1974) extend the option value concept to that of a ‘quasi-option’ in situations that are irreversible, and actions in one period affect what occurs in the next period. They discuss the uncertainty of harms, and demonstrate that in a cost-benefit analysis of alternatives, the presence of irreversibility reduces the potential benefits of that action. Kolstad’s (1996) paper on learning and stock effects in environmental regulation state that when we are faced with irreversible effects, *“We should avoid decisions that restrict future options”*. The findings in these papers demonstrate the importance of exploring the value of actions that incur a cost today, but that give us options in the future to mitigate climate change. Investments in CCS when it is not yet economically competitive are one such an example, where deciding not to invest could result in the irreversible effect of having to build out the technology at greater costs in the future, or lock-out when the technologies are simply to expensive to ever be built out. Therefore, as Arrow and Fisher state, this quasi-option value must be incorporated into a cost-benefit analysis accordingly.

A comprehensive review of studies that explore sequential decision-making and learning applied to climate policy is presented by O’Neill et al (2006). The studies reviewed focus on the general discussion of whether it is better to wait rather than to act to mitigate climate change, and how learning pertains to the issue.

Hammitt et al. (1992) explore sequential decision-making in climate policy as a two-stage decision analysis, with the decision of an aggressive or moderate policy in the first stage, and the opportunity to make the climate policy stricter or looser in the second stage. The paper investigates whether an aggressive or moderate emissions policy today is overall more costly, depending on global the temperature’s sensitivity to CO_2 emissions.

Yohe (2004) explores the value of early mitigative action as an insurance policy, and similarly to Hammitt explores a two period decision process where the climate policy can be changed in the second period. The paper compares the costs of meeting different emissions targets with and without early policies, when we learn by the second stage what the emissions target should be.

The focus of these studies is specifically on mitigation actions, and Hammitt et al. (1992) and

Yohe et al. (2004) in particular employ a decision framework very similar to the one in this study. This thesis provides an alternative perspective however, by examining the decision to support investment in a clean technology[1] when an emissions policy is already in place, rather than decisions on general mitigation policies.

Therefore the question of how uncertainty can affect costs to society for mitigating climate change has been examined, but not specifically for CCS investment with a CGE model that takes account capacity building in a similar way to learning-by-doing, such as EPPA. An important aspect to take note of is that this thesis assumes that the government is able to adapt the emissions policy, either from taking note of new information on the science of climate change or because political preferences have changed. We must recognize that this may not always be the case in reality, and that adaptive policy making is not a widely followed practice as it is often harder to implement than static policies, and is associated with many political hurdles (McCray & Oye, 2006; Foster, 1999).

2.3 Modeling investments in energy technologies

There is a wealth of literature on modeling subsidies and financial support for clean energy technologies. Often there is little distinction in modeling the type of funding for a technology, specifically whether the source of funds is from private companies or the government. This section discusses the existing studies on modeling funding of technologies, whether from the government or the private sector. Within the substantial suite of existing analyses, none focus on the impacts of subsidies and investment in the presence of a combination of uncertainty and learning-by-doing.

Reports discussing energy technology investments often analyze the optimal combination of policies that support clean technologies, and policies that place a price on carbon, for maximizing total welfare. According to economic theory, in a world with no market imperfections other than the environmental externality of CO_2 emissions, a carbon tax or a cap

[1]See section 2.5 for a discussion on why CCS investment in particular is a worthwhile technology for this investigation

and trade is the optimal policy tool for abating emissions, as it directly addresses the market failure (Nordhaus, Forthcoming). Even if we assume that the true cost of carbon emissions are known so that an appropriate price can be achieved and the market failure internalized, it is unrealistic to assume that there are no other market imperfections.

One example is that advanced technologies that require R&D will be underinvested due to spillovers, which are situations in which the benefits of investment do not accrue exclusively to the investor. If left to the private sector to make all R&D investments in new energy technologies that will be needed to address climate change, the presence of spillovers will cause underinvestment, and the necessary technologies may be unavailable or higher cost (Spence, 1984). Kverndokk et al. (2004) investigate the optimal balance between subsidies and carbon taxes in a CGE model to address these spillover effects.

Another related issue frequently discussed is how investment can affect technical change. Jaffe et al. (2002) provide a summary of studies that have examined how R&D subsidies can induce technical change under various circumstances with different economic models.

A further question often asked is whether subsidies, as a specific form of investment, should be directed to particular technologies or within a more general R&D budget. Schneider and Goulder (1997) argue that subsidies should only be applied to industries where spillover effects are prevalent, and that it is unclear whether energy technologies in particular have greater spillover effects than any other industry, and therefore targeted subsidies are not the optimal solution. However Acemoglu et al. (2009) argue that as long as the elasticity of substitution is high for clean or dirty inputs, the results from their two-sector growth model show the optimal policy to mitigate CO_2 emissions is to subsidize clean technologies, as well as imposing a carbon tax.

Although these studies provide information on whether and how funding should be implemented to encourage CO_2 emissions abatement, they do not discuss the question of investment when there are uncertainties in the future and the existence of a learning-by-doing effect, which is a central issue explored in this thesis.

2.4 Modeling learning-by-doing

The existence of learning-by-doing could provide value from early investments in clean energy technologies, as a hedge against having to meet greater demand in the future when the technology is still expensive when there has been no earlier learning.

This section explains how cost reduction through learning-by-doing is represented using several techniques across different model structures, and how this phenomenon has been investigated to date.

The IEA states:

"If we want cost-efficient, CO_2-mitigation technologies available during the first decades of the new century, these technologies must be given the opportunity to learn in the current marketplace. Deferring decisions on deployment will risk lock-out of these technologies, i.e., lack of opportunities to learn will foreclose these options making them unavailable to the energy system" (2000).

This thesis tests this argument, by examining how CCS investment will enable the technology to experience cost reductions, in order to prevent having to use it when it is still expensive if demand suddenly increases later. 'Lock-out' refers to a state where the technology is simply too costly to ever penetrate the market. If climate policies become stricter in the future, there will indeed be a demand-pull for CCS, and it will be available in some sense as each of the components of CCS are proven and established (see section 2.5.3) but it will not have reached technological readiness and costs will still be close to first-of-a-kind.

Learning-by-doing, where costs are reduced with experience, is a generally accepted phenomena supported by empirical evidence (Gillingham et al., 2008). It is represented in models in various ways as a form of technical change. Endogenous technical change (ETC) implies a feedback system whereby technical advances and progress depend on processes in the model. If policies kick-start these processes, then the policies can induce technical change through ETC (Köhler et al., 2006). Alternatively, exogenous technical change, often calibrated to reflect historically observed rates of efficiency improvements, can be applied to the model. An example of this is the autonomous energy efficiency improvement (AEEI) factor found in many CGE models including the MIT EPPA model (Paltsev et al., 2005a). For further information on the AEEI, see the detailed explanation written by Azar and Dowlatabati (1999).

Investment in technologies can promote innovation and affect a technical change, which can be treated in models as R&D or learning-by-doing. Approaches that model innovation through R&D are usually implemented with forward-looking dynamic models where a policy of R&D incurs a cost. For this purpose R&D innovation is represented as an investment in knowledge stock, which is an input into production, just like capital, labor or energy. Modeling innovation as R&D requires consideration of market failures such as spillovers, and crowding out, where R&D in one sector reduces the R&D in another (Köhler et al., 2006). Models that represent technical change as R&D include versions of the Regional Integrated Climate Economy model (ETC-RICE) (Buonanno et al., 2003) and the Dynamic Integrated Climate Economy Model (R&DICE) (Nordhaus, 2002), ENTICE (named after ENdogenous Technical Change) (Popp, 2004, 2006), Otto and Reilly's dynamic general equilibrium model (2006) and the CGE model developed by Sue Wing (2003).

The market imperfections of spillovers and crowding out, and the fact that returns to R&D are not definitive and require much data to model, means representing technical change through R&D in non-forward looking models with many sectors and regions is an extremely challenging task.

Therefore, many non-forward looking models, with multiple energy technologies tend to use learning-by-doing through empirically determined experienced curves, rather than explicit R&D and knowledge stocks, such as EPPA (Jacoby et al., 2006), NEMS (EIA, 2009c) and MESSAGE (Grübler & Messner, 1998).

Zwan et al (2002) compare how including learning-by-doing as an endogenous effect impacts reaching climate targets and explore what subsidies to non-fossil energy technologies we would need to meet emissions targets. This thesis builds on this research by using a model where capacity building is represented in a way that has similar properties to learning-by-doing, while incorporating the element of uncertainty and focusing specifically on CCS rather than a general non-emissive technology. Further, this thesis calculates a value for the investment in terms of welfare, in order to allow comparison of choices of whether to invest or not.

Modeling technical change through learning-by-doing or R&D both have relative advantages and disadvantages. R&D has an explicit opportunity cost associated with the activity, which many believe to be a more appropriate representation of technical change than learning-by-doing, which is costless. However, modeling R&D through knowledge stocks requires a great deal of data on the relationship between investments and the outcome of innovation, which in many instances does not exist or is difficult to obtain in sufficient detail. Learning curves can be estimated from observing the cost reduction in technologies over time. Further, learning-by-doing can also capture costless innovation, where simple experience can lower costs when explicit cash injections are not provided, whereas no innovation modeled with R&D is represented as free. On the other hand, although learning rates can be applied exogenously to models, the causal relationship between cumulative capacity and cost reductions is not proven, and it is difficult to conclude that no other factors are involved.

There is no conclusive evidence that one method is superior to the other. The model used for this analysis represents technical change and cost reductions using a method that creates an effect similar to learning-by-doing approach, where costs are reduced as capacity is built up (see section 3.1.2). This study furthers the discussion on technical change by examining how an investment can affect social welfare when a representation of learning-by-doing is a feature of the model, and future uncertainties are taken into account.

2.5 Carbon Capture and Storage – a relevant technology

This thesis explores how investment in CCS could provide the option of meeting stricter climate targets in the future at lower cost, and therefore whether investments could be beneficial to society as a whole if we recognize the uncertainties of the future.[2] CCS is a particularly interesting technology to investigate as a case study of the effects of early investment under uncertainty, as it is currently prohibitively expensive and has undergone no learning and cost reductions so far. It could also have huge potential as a low CO_2 emissive energy source, and it is currently receiving a great deal of attention politically and commercially as discussions of climate legislation continue.

2.5.1 Costs

Since CCS is not an established technology there is no agreed-upon consensus as to its cost. However all studies on cost estimation find it is more expensive than other baseload energy technologies currently being used. Hamilton et al. (2009) find a levelized cost of electricity (LCOE) of pulverized coal with CCS as 100$/MWh, compared to 62$/MWh for a reference plant without CCS. A Harvard Kennedy School study estimates the LCOE to lie within the range 160-200$/MWh, as opposed to 80$/MWh for a reference supercritical pulverized coal plant without capture (Al-Juaied & Whitmore, 2009). Therefore, although there is disagreement over the absolute figures, studies agree that CCS technologies are considerably more expensive than conventional coal-fired generation, the US's main current baseload energy technology.

Because CCS is more expensive than alternative baseload technologies already available, policies would be needed to lower costs before it would compete in the market place. This would be carried out either through technology-pull by creating a market through placing a price on carbon, or through technology-push by spurring innovation with early investment, or a combination of the two, therefore making it a perfect candidate to examine whether investment today can affect welfare costs in the long term under uncertainty. Hamilton et al. (2009) calculate a carbon price of 65$/tonne CO_2 to make it competitive with supercritical pulverized coal (including transportation and storage). With a current carbon price of 0$/tonne CO_2 nationally in the US, and a clearing price of a mere 2.07$/ton CO_2 within the Regional Greenhouse Gas

[2] It is important to note that the framework presented in this study should be extended to assess investment portfolios across many technologies, in order to determine the optimal investment strategy. See section 5.1 for a more detailed discussion.

Initiative in the March 2010 auction, (RGGI, 2010) policies that encourage investment are necessary for CCS technology to become economically competitive in the near term, as the demand-pull does not exist.

2.5.2 Potential to be large scale and low emission energy source

Demand for CCS in the USA under a stringent CO_2 policy could be very high, as it could provide baseload power, with a relatively cheap and abundant fuel, with up to 90% lower emissions than conventional coal power. This desirable combination motivates the conjecture that, should emissions paths become much stricter in the future, demand for CCS could rise dramatically, and therefore it is useful to explore the role of CCS in the future energy mix using models.

The MIT Future of Coal study (Moniz & Deutch, 2007) modeled how the economy would react to a carbon emissions policy in worlds both with and without the option of using CCS, where nuclear power is first artificially constrained to reflect the US's general lack of support of nuclear power, and then allowed to grow to meet market demand. This was investigated using the MIT EPPA model. Modeling a carbon tax policy, the study found the following results in 2050:

Table 1. MIT Future of Coal Report findings

	Limited nuclear power		Expanded nuclear power	
	CCS available	CCS not available	CCS available	CCS not available
Coal consumption in USA (EJ)	40	28	25	13
Global CO_2 emissions (Gt/yr)	28	32	26	29
CO_2 emissions from coal (Gt/yr)	5	9	3	6

In order to provide the reader with the context to compare coal consumption, in 2009, the US consumed approximately 8 EJ of coal (EIA, 2010). There are two central points to take from this table. The first is that when there is an emissions policy, and CCS is available, in 2050 the US economy is able to consume much more coal, (40 EJ versus 28 EJ, and 25 EJ versus 13 EJ) which is cheap, domestically sourced, and abundant. Even when nuclear technology is expanded, the ability to use CCS allows us to consume far more coal than we would otherwise be able to. Coal currently provides about 50% of the US electricity supply, and framing the discussion of alternative technologies and policies that enable us to meet emissions targets in such a way that we avoid deviating from our status quo of energy supply as much as possible is relevant, as it can involve meeting emissions targets at lower costs. Secondly, we can see that CO_2 emissions are lower both in general, and specifically from coal, when CCS technology is available.

These results illustrate the potential that CCS could have for meeting our emissions targets. Therefore, since it could be an important technology in our future if we do implement climate legislation, exploring methods that could enable us to use it more cheaply, such as early investment to accelerate learning, is a worthwhile endeavor.

2.5.3 Current state of the technology

CCS is currently nowhere near the level of technological readiness for energy generation at n^{th}-of-a-kind costs. Since CCS is yet to reduce costs through learning, we are in a unique position where we can make decisions today, while the technology is still in its nacency that give us different options in the future. Therefore CCS is an appropriate case study for examining how early investment can affect learning and overall costs to society, as the results can inform the very real policy decisions we can make today.

The following section relies on information provided in 'Carbon Dioxide Capture and Storage' by Herzog (2009). A fully integrated CCS system involves capture, transport, injection and monitoring. Today, there are very few fully integrated systems at scale, although each of the above activities is well established in isolation. Different technologies for CO_2 capture, such as post-combustion, oxy-combustion and pre-combustion are all technologies that exist today. CO_2 capture is used for enhanced oil recovery (EOR), where the captured CO_2 is injected into almost depleted oil fields to enable the extraction of more oil by building pressure. There are over 3,400 miles of CO_2 pipelines in the USA to carry CO_2 to oilfields specifically for EOR, mostly located in Texas, Colorado, Wyoming and North Dakota. The injection of CO_2 in geological formations has been practiced both through EOR and the injection of acid-gas, a by-product of oil and gas production mostly comprised of CO_2. There are monitoring methods in existence today capable of observing stored CO_2, such as time-lapse 3D seismic monitoring, passive seismic monitoring, and crosswell seismic monitoring.

Despite our capabilities at operating the individual components of a full CCS system, there are only four commercial scale[3] integrated CCS systems in existence today and none are associated with power production.

[3] Here, large-scale means that more than 1 million tonnes of CO_2 are stored per year.

- Sleipner, North Sea, Norway: CO_2 from natural gas processing for geological storage in saline aquifers
- Weyburn, Saskatchewan, Canada: CO_2 from coal gasification for EOR
- In Salah, Ouargla, Algeria: CO_2 from natural gas processing for geological storage
- Snøhvit, Barents Sea, Norway: CO_2 from natural gas processing for geological storage

Since there are only four large-scale scale projects to date, it is clear that the technology is not yet widely available. Further all these projects are commercial because of revenue gained from either natural gas production or from EOR, and not solely for CO_2 storage, since today there is no value for carbon. CCS units will not be built for purposes other than acid-gas injection and EOR, until regulations are put in place that put a price on carbon.

Since there is low demand for CCS today, the associated legal, regulatory and liability measures necessary for deployment at a large scale are not yet in place. However in July 2008 the EPA published a Proposed rule for Federal Requirements under the Underground Injection Control (UIC) Program for CO_2 sequestration for public review and comment. Although this is a step in the direction to ease diffusion of CCS, the regulations would not address the issue of legal ownership, as currently the legal right to use the pore-space in the subsurface requires the permission from any land owner where the CO_2 could possible migrate to, which could be practically impossible to determine. Furthermore there is currently no governmental mechanisms set up to ensure long-term liability of the storage site.

Since the technology is clearly far from being established at scale, further learning is required to reduce costs, and this will not happen unless demand increases, spurred by a high enough carbon price, or a technology-push policy such as early investment is implemented. CCS is therefore a relevant technology to examine how investment could affect the overall costs of meeting climate targets when there is uncertainty.

2.5.4 Political relevance

CCS as an energy technology has recently received a lot of attention in Congress. The American Reinvestment and Recovery Act 2009 allocated \$3.4B in total for RD&D in clean fossil energy projects. The following table by Hamilton et al. (2009) provides details as to how the funds were divided:

Table 2. Fossil RD&D funding allocations under the American Reinvestment and Recovery Act 2009

Fossil Energy RD&D Program	Amount
FutureGen	\$1,000,000,000
Clean Coal Power Initiative	\$800,000,000
Industrial CCS	\$1,520,000,000
Geological Characterization	\$50,000,000
Geological Training	\$20,000,000
Program Funding	\$10,000,000
TOTAL	\$3,400,000,000

The American Clean Energy and Security Act HR2454, passed in the House of Representatives in June 2009, provisioned somewhere in the range of \$240B from 2012 through to 2050 in financial incentives for CCS (Pew Center for Global Climate Change, 2009) demonstrating that the discussion of investment in CCS is indeed an issue that is highly topical at this time, and attempts to value the policy options are important to ensure government takes the least cost actions.

The issue of promoting or opposing financial support for CCS is a politically charged debate with strong opinions on both sides. The US has a large coal industry with a significantly powerful lobby in Congress. Investments in CCS could be defended by the claim that it is an abundant resource domestically found, while others would argue it is a dirty fuel that we should attempt to wean our economy from as soon as possible, and therefore investments in any coal technology are detrimental to our welfare. This study makes no value judgment on the worthiness of CCS as a technology, and only examines the value of investments in a purely economic analysis.

CCS is a relevant technology for examining whether early investments can reduce the overcall costs of meeting emissions paths through learning-by-doing, because it is not an established technology at scale, and cost reductions due to learning are yet to take place. Further, it is currently expensive, and has potential to play a large role should CO_2 policies be implemented. CCS faces significant barriers before being widely deployed, and therefore the study of technology-push policies such as direct investment is relevant.

In summary, this thesis builds on existing reports on energy technology forecasts by including the element of uncertainty, and a framework for how to make policy decisions. This work also expands on the previous studies on modeling technical change by exploring specifically how CCS investment can change the costs to society of meeting emissions targets, rather than focusing on mitigation only. This study also discusses modeling of financial support within the realm of uncertainty, rather than discussing only the traditional issues of directional subsidies versus general R&D. Finally, the thesis extends the existing literature on learning-by-doing by examining how early investment can affect welfare costs when uncertainty is taken into account, using a CGE model that includes a form of innovation in a way that produces results that are comparable with representation of learning-by-doing.

3 Analysis method

This study applies a decision analytic framework to explore the conditions under which it would be welfare improving to invest in CCS today, rather than not investing, using results from a computable general equilibrium (CGE) model. I construct a single-stage decision tree where the decision today is whether to invest in CCS or not, and each branch of the tree presents alternative assumptions about the state of the US energy system and climate policy. These assumptions provide inputs to the CGE model, which gives output measures of societal welfare for each scenario. The percentage change in the welfare from the No Policy scenario is the metric by which each branch of the tree is compared against all the other branches. By varying the probabilities for the uncertainties, it is possible to solve the decision tree for each circumstance to find the range of probabilities when it is beneficial to invest today, and when it is not.

This chapter describes in detail the CGE model used for the different scenarios, as well as the decision model. The remainder of the chapter explains how the outputs from the model are integrated into the decision analysis.

3.1 EPPA model

The EPPA model is a multi-region, multi-sector, recursive dynamic representation of the global economy (Paltsev et al., 2005a). EPPA was developed by the MIT Joint Program on the Science and Policy of Global Change and is designed to analyze economic growth under different policies and scenarios. EPPA is a computable general equilibrium (CGE) model, and thus represents the circular flow of goods and services within the economy, as they flow from the producing sectors to the consumers, who then provide capital and labor as factor inputs back to the producers. Consumers receive income for their capital and labor, and producers receive payments for the goods and services. The base year of the model is 1997 and it solves in 5-year time steps from 2000 to 2100. EPPA models six greenhouse gasses (CO_2, CH_4, N_2O, HFCs, PFCs and SF_6) and can therefore examine the effects of policies targeted at greenhouse gas emissions abatement beyond just CO_2.

EPPA is aggregated into sixteen different regions across the globe, with twelve economic sectors and nine electricity-generating technologies. Table 3 lists these attributes (for further details see Paltsev et al., 2005a).

Table 3. Regions, sectors and energy technologies represented in EPPA

Country/region	Sectors	Energy technologies
United States (USA)	Agriculture (AGRI)	Conventional fossil
European Union (EUR)	Energy Intensive (EINT)	Hydro
Eastern Europe (EET)	Transportation (TRANS)	Conventional Nuclear
Japan (JPN)	Other Industry (OTHR)	Advanced Nuclear
Former Soviet Union (FSU)	Services (SERV)	Wind, Solar
Australia and New Zealand (ANZ)	Electricity (ELEC)	Biomass
Canada (CAN)	Conventional crude oil (OIL)	NGCC (natural gas combined cycle)
India (IND)	Oil from shale (SOIL)	NGCC with CCS
China (CHN)	Liquid fuel from biomass (BOIL)	Coal with CCS
Indonesia (IDZ)	Refined oil (ROIL)	
High Income East Asia (ASI)	Coal (COAL)	
Mexico (MEX)	Natural gas (GAS)	
Central and South America (LAM)		
Middle East (MES)		
Africa (AFR)		
Rest of World (ROW)		

As a top-down CGE model, EPPA captures important feedbacks between sectors of the economy that are not represented in the other models that have reported technology forecasts, such as Socolow and Pacala (2004) and EPRI (Douglas, 2007). In particular, EPPA explicitly accounts for the opportunity costs of shifting capital and labor between sectors, which is critical in estimating the value of early investments in a technology before it becomes economically competitive.

Three components of the model are relevant to the question examined in this study: the representation of electricity production and energy technologies, the representation of capacity building constraints and learning-by-doing, and the representation of early investment. Each of these is described in more detail below.

3.1.1 Energy technologies in EPPA

Under carbon constraining policies, advanced low-carbon energy technologies will replace conventional sources of energy, as the costs of the new technologies decrease relative to conventional energy technologies in use today. This section explains how these energy technologies are modeled.

The nine energy technologies represented are separated into 'existing' and 'advanced' categories, depending on their availability in the base year and how they are modeled, and are shown in Table 4. Only Conventional Fossil, Hydro and Conventional Nuclear are available in the base year, and are thus defined as existing, while the remaining technologies become available in future periods to reflect estimates of the timeframe by which the technology is proven on a small scale (albeit not yet necessarily economically competitive). The representation of the advanced technologies is often referred to as a 'backstop', traditionally defined as a technology that at a certain price can deliver energy from an effectively infinite resource base.

For the USA, which is the focus of this study, the 'Conventional Nuclear' energy technology represents the nuclear power plants already in existence, and is artificially constrained to reflect the country's historical lack of willingness to build more nuclear plants (Delmas & Heiman, 2001). The 'Advanced Nuclear' backstop represents the next generation of nuclear fission power plants, and its penetration is determined by its relative costs to other technologies.

The costs of the technologies, which dictate how competitive they are and their resulting share of production, are determined in part by two sets of exogenous parameters defined in the base year. The first parameter is the markup factor, which is defined as the incremental cost of the n^{th}-of-a-kind plant. The markup is the ratio of the levelized cost of electricity (LCOE) for that technology to the LCOE of traditional coal-fired generation, which provides most of the baseload power supply in the US today. Any electricity-generating technology that is more expensive than coal, will have a markup greater than 1. The markups are shown for each technology in Table 4. The markups are calculated using the costs from the EIA assumptions to the Annual Energy Outlook 2009. The mark ups are calculated using the LCOE model by Morris et al. (Forthcoming), which uses inputs from the EIA Annual Energy Outlook (2009b)[4]. The basic technologies are not modeled in the same way as the advanced technologies, (see Figure 1) and so their costs are not defined by markups (except for conventional fossil, which is by definition the baseline for comparison for the other technologies, and is therefore 1).

Table 4. Costs and availabilities of energy technologies in EPPA

Energy technology	**Technology type**	**Availability**	**Markup**
Conventional Fossil	Existing	Base year	1
Hydro	Existing	Base year	-
Conventional Nuclear	Existing	Base year	-
Biomass	Advanced	2010	1.5
Wind and Solar	Advanced	2010	2
Advanced Nuclear	Advanced	2020	1.85
NGCC	Advanced	2010	1.02
NGCC with CCS	Advanced	2015	1.43
Coal with CCS	Advanced	2015	1.54

The second set of parameters is the cost shares of the primary factors of production for each technology. For Conventional Nuclear and Hydro, only the shares specify the costs of the technology, as they do not have markups. The primary factors of production are shown in the nesting diagrams below (Figures 1-5) and include capital, labor, fuel, land and several others depending on the technology. The input shares for all the energy technologies are also calculated from the same inputs as the markup. The cost of electricity (COE) is calculated by summing the costs for that technology provided by the inputs used in Morris et al. (Forthcoming) in $/kWh.

[4] A different heat rate is assumed for Coal with CCS in calculating the LCOE – specifically the heat rate used in (Hamilton et al., 2009). This is because the heat rate given by the EIA is very low, and results in a LCOE much lower than other estimates in the literature. Similarly, the markup for Advanced Nuclear is determined independently from the LCOE model. See section 8.1 in the appendix for details.

The capital share is the capital costs divided by the COE, labor share is the operation and maintenance cost divided by the COE, and the fuel share is the fuel cost divided by the COE. For technologies with separate transmission and distribution, these costs are split between capital, with 62%, and labor with 38% (McFarland & Herzog, 2003).

These shares are defined initially in the base year of the model using the EIA estimates of the costs, and as the price of each input changes over time, the contribution from each input changes as a function of the elasticity of substitution (the • values in the diagrams below) and the total cost of the technology will also change as a result.

The nesting diagrams of the electricity sector and energy technologies that follow are taken from Paltsev et al. 2005a, and show the breakdown in primary factor inputs for each energy technology. Vertical lines in the input nest signify a Leontief structure where the elasticity of substitution is zero. Terminal nests with "…" indicate the same aggregation structure for imported goods as the Energy Intensive sector, EINT. OIL (conventional crude oil) is modeled as an internationally homogenous good, and therefore there is an infinite elasticity of substitution between OIL produced in each region. (Paltsev et al., 2005a).

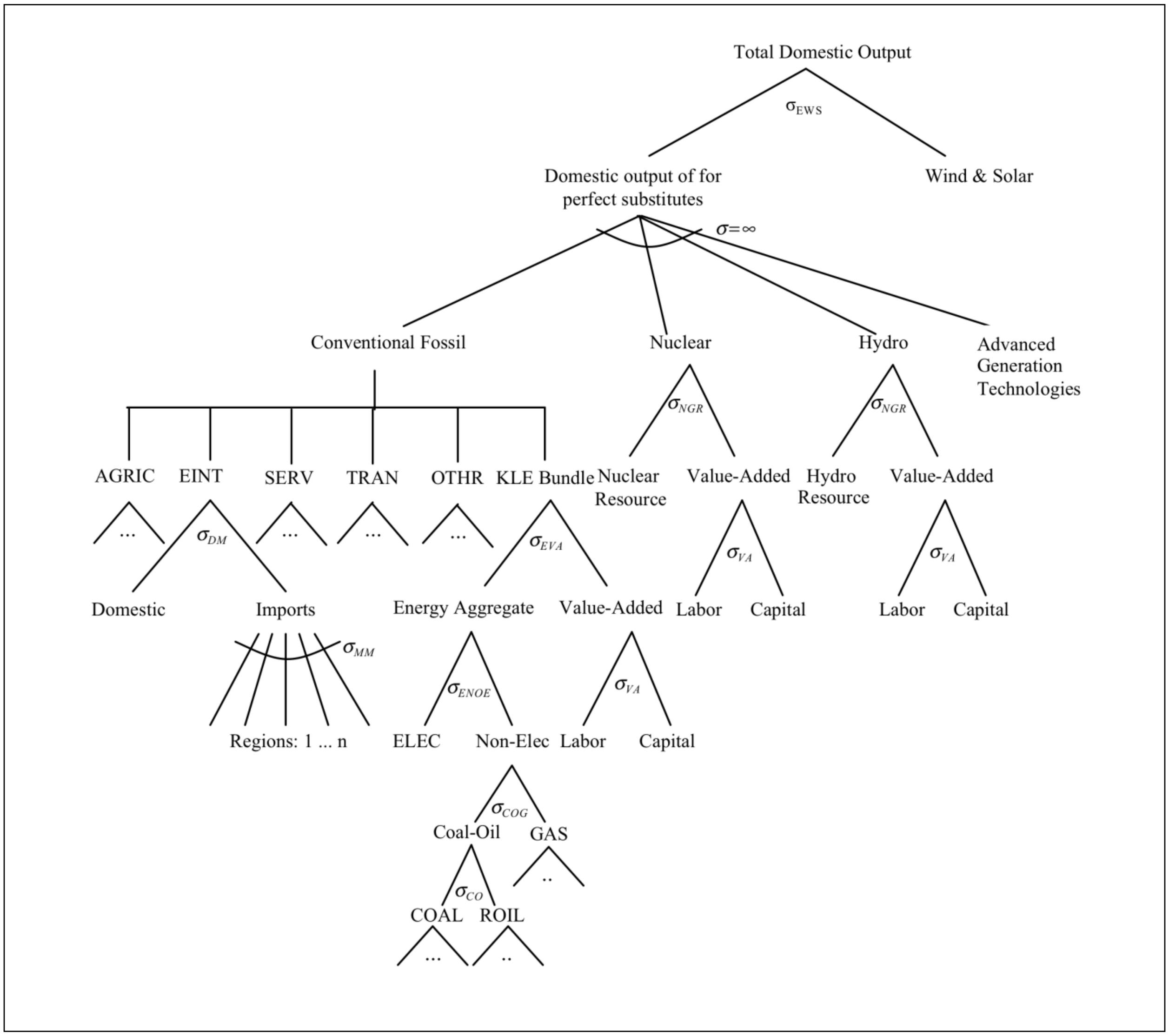

Figure 1. Electricity sector nesting diagram

The diagram shows the electricity sector in EPPA. All the advanced technologies except for wind and solar, act as perfect substitutes for the existing technologies (• = •). Since both technologies are intermittent, they are imperfect substitutes for other energy technologies, and are grouped together as one advanced energy technology. Wind and solar's overall penetration, which is controlled by the elasticity of substitution $\bullet_{EWS}$, is therefore limited in the model because of this issue of intermittency.

Electricity production from Conventional Fossil technology is not modeled separately for coal, gas and oil generation technologies. Instead it is modeled as a single production technology with substitutions among the fuels as inputs to production. This has the effect of limiting fuel switching from one to the other, in order to represent baseload, intermediate and peaking fossil power. For example, even if gas is expensive, this nesting structure will preserve its use, which reflects the fact that coal or nuclear cannot be used for peaking units because of high fixed costs and ramping constraints.

The Conventional Nuclear and Hydro technologies are simple production functions where the main inputs are labor and capital, which can substitute for each other within the value-added bundle, and the energy resource for that technology. Hydropower is artificially constrained in EPPA, as the model assumes that the potential for hydro capacity in the US is exhausted. Conventional Nuclear is constrained for the political reasons given above.

The advanced generation technologies have distinct nesting structures, which are shown in Figures 2-5. Electricity from biomass, and the wind and solar backstop have the same nesting structure. The Fixed Factor, which is an input in the nesting structures, is described in detail in section 3.1.2. The transmission and distribution is implicitly included in the capital and labor inputs for the biomass, and wind and solar backstops.

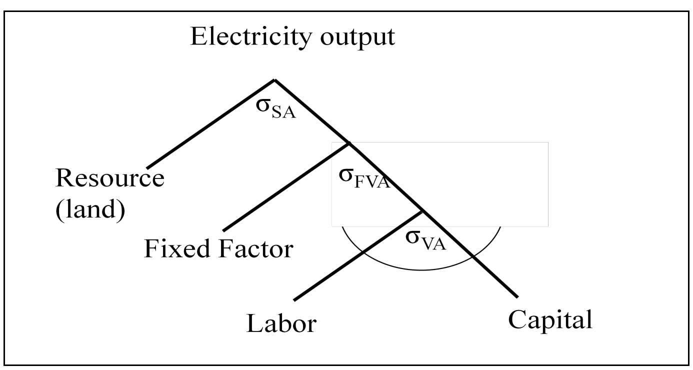

Figure 2. Biomass, wind and solar nesting diagram

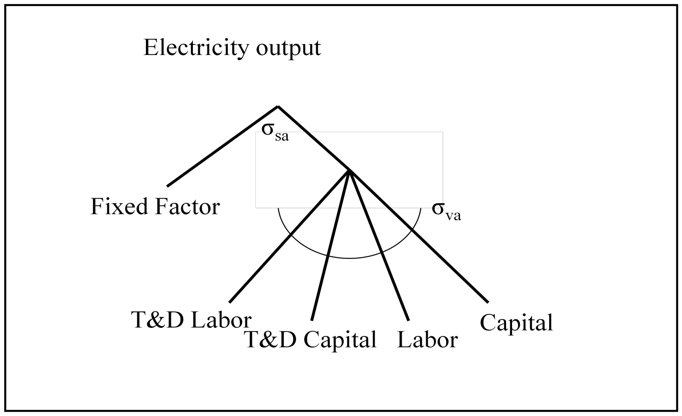

Figure 3. Advanced Nuclear nesting diagram

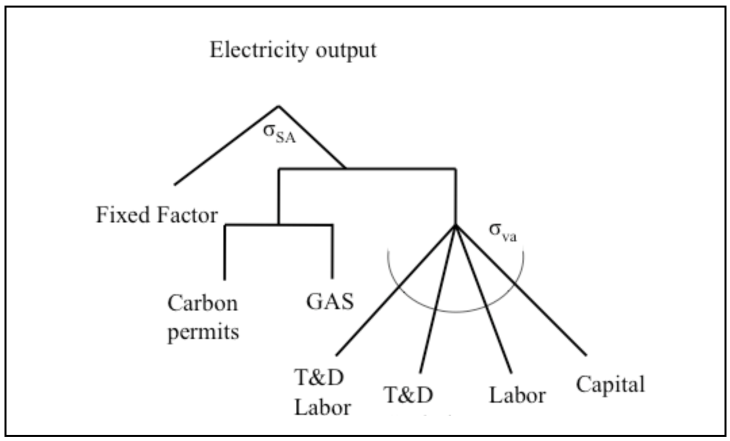

Figure 4. Natural gas combined cycle (NGCC) nesting diagram

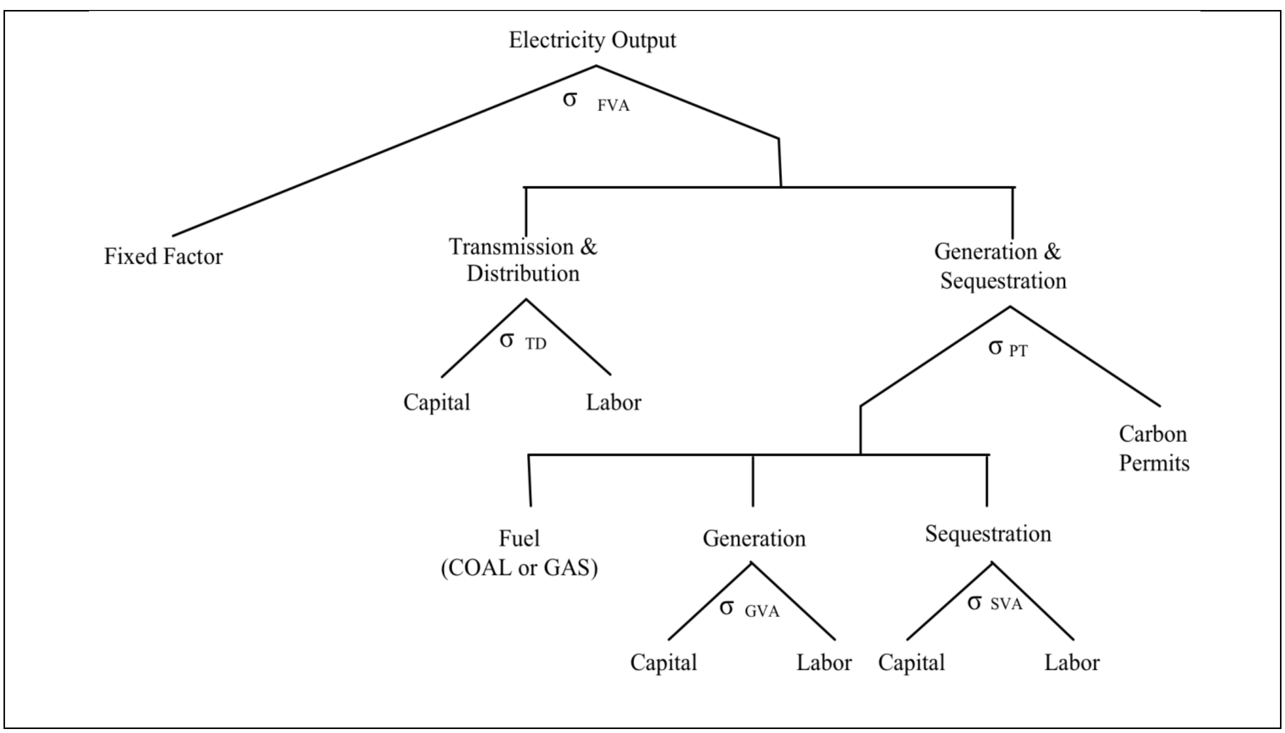

Figure 5. Carbon capture and sequestration technologies nesting diagram

Figure 3 shows the Advanced Nuclear nesting diagram. Transmission and distribution is separated out from generation capital and labor for greater flexibility. There is no fuel share as uranium is considered abundant, a small component of the total share of the costs, and reliable data tracking uranium costs is difficult to obtain.

The nesting diagram for NGCC is shown in Figure 4, and the advanced fossil technologies with CO_2 capture and storage, Coal with CCS and NGCC with CCS, is shown in Figure 5. Although the NGCC with CCS backstop represents specifically natural gas combined cycle technology with carbon capture and storage, the Coal with CCS backstop is not confined to a particular technology. Today, it is not clear which advanced coal technology with CCS will become most economical, out of integrated gasification combine cycle, pulverized coal, or oxy-fuelled. Therefore the backstop in EPPA represents a generic advanced coal technology with CCS, rather than a specific one. An input for carbon permits is required for the fossil technologies as all of them all emit $CO_{2,}$ including those with CCS since we assume an initial capture rate of only 90%. The carbon permits enter as a Constant Elasticity of Substitution (CES) production function with generation and sequestration for the CCS technologies. This is because the model assumes that capture rate increases from 90% as the carbon price gets very high. Unless modeled in this way, there is technology switching back to gas as the carbon price rises, when it is realistic to assume that CCS plant designers would improve the capture efficiency if emitting 10% of CO_2 produced would cost market share and fuel switching away from their plants. By using this nesting structure, as the price of carbon permits increases, more generation and sequestration inputs are used, to reflect increasing capture efficiencies. For the conventional fossil technologies, and the NGCC backstop, the carbon permits enter with a zero elasticity of substitution with the fuel resource as these technologies, similarly to NGCC, do not capture any CO_2 and are therefore unable to make any substitutions as the price of permits increases. By convention and for simplicity, these permits are only shown in the nesting diagrams for advanced fossil fuels. Similarly to Advanced Nuclear, the transmission and distribution activities for advanced fossil fuels are separated out for greater flexibility.

3.1.2 Representation of capacity building constraints in EPPA

EPPA does not include formal models of either R&D or learning-by-doing (see a review of these approaches in section 2.4). However, EPPA does constrain capacity building of energy technologies in a way that gives rise to similar effects as learning-by-doing under some conditions. This section describes the representation of the capacity building constraint in EPPA through the use of an additional production input called the 'fixed factor'.

Jacoby et al. (2006) distinguish between two processes that affect technology diffusion. The first is an adjustment cost, which affects the rate at which the technology enters the market independently of whether the costs of the technology change with experience over time. The second is the process of innovation by which the costs of the technology may reduce as experience is gained an innovation occurs, which could be represented in a model either as R&D and knowledge stock, or through experience as learning-by-doing. The fixed factor parameter is a means of representing both of these effects, adjustment costs and innovation, with the latter taking a form similar to learning-by-doing rather than R&D. The result is a factor input that contributes to the capacity building of energy technologies in EPPA.

In an economic model with no constraints on capacity building, in the very first period where a technology has a lower cost than the alternatives, it would immediately constitute a large share of total production and enter the market very rapidly. This is an unrealistic pattern of capacity building, as in reality there are adjustment costs that must be accounted for. The price of specialized resources that are required for capacity building such as knowledgeable engineering, specialized manufacturing and services will affect the rate of penetration of that technology into the market (Jacoby et al., 2006). The fixed factor is used to represent the specialized resources. If the demand for the technology is high, the price of the fixed factor representing the limited resources will also be high, thereby constraining the rate of initial expansion of production from new energy technologies and taking account of the adjustment costs.

The fixed factor also represents innovation in the form of learning-by-doing, as it results in a constraint that is less binding as production and experience is gained. The representative agent is endowed with a very small amount of the particular fixed factor resource for each technology in the base year, $FF_{t=0}$. The amount of fixed factor then is increased as a function of cumulative production of that technology, representing cost reduction as we learn and gain experience.

The fixed factor combines these two affects to constrain how capacity is built. When the technology first becomes cost-competitive, and only a small amount of capacity has been built, the fixed factor endowment is low which causes the production costs to be above the long-run level. The higher cost slows the rate of increased production from the technology to account for the adjustment costs described above. Once the production exceeds a critical level, the endowment will become large enough that the fixed factor is no longer a binding constraint, and the production cost will decrease to the markup value specified for each technology (Paltsev et al., 2005b).

The fixed factor, as a hybrid parameter to represent learning-by-doing and adjustment costs, therefore models capacity building for energy technologies. In terms of technology adoption, the effect is the same as using a model that represents learning-by-doing more conventionally, in a form separate from adjustment costs. In EPPA, the technology costs are initially higher when the technology is new and before much experience is gained, and then costs fall with increasing cumulative production, which is the same in a model representing learning-by-doing explicitly. However, the fixed factor also allows rents to accrue to the limited number of agents with the ability to build the technology when it is still new (providing a first-mover advantage) and when there is no widespread technical knowledge to build cheaply at large scale, due to the adjustment cost aspect. Traditional modeling of learning-by-doing does not represent these rents, as they are part of the adjustment costs, and so the fixed factor provides an extra effect on top of cost reduction through experience.

Furthermore, if production is increased at a sufficiently slow rate, the fixed factor will not be constraining since the price of the specialized resources will not be high. This contrasts with learning-by-doing where the initial high costs fall as a function of cumulative production, independent of the rate of expansion. Nevertheless, the typical behavior of new technologies entering the market is an ‘S-shaped’ curve (Grübler et al., 1999), with slow expansion at first followed by an accelerated uptake. The fixed factor is designed to emulate this logistic S-shaped pattern of penetration of new technologies, and therefore since expansion is of this form, demand is usually high enough such that the fixed factor is almost always constraining and therefore produces the associated learning-by-doing effects.

Since the fixed factor is constraining is most cases, and because the effects in terms of technology build out are the same as for a model representing learning-by-doing independently from adjustment costs, the fixed factor allows the exploration in this thesis of the interaction of learning-by-doing with early investment under uncertainty.

The rate of production increase of an advanced technology is determined by the fixed factor in two ways. The first is the equation that dictates how the resource endowment grows as a function of increasing output. The equation for endowment is of the form (Paltsev et al., 2005b):

$$FF_{t+1} = FF_t + \bullet(aY_t + bY_t^2)$$

Y_t is the electricity output for a given technology in period t. a and b are coefficients that determine the rate of penetration for the technology, empirically found to reflect an energy technology adoption rate of quadratic form that results in the same qualitative 'S-shape' curve as penetration rates found in the literature. It is illustrative in design and is not intended to represent a specific adoption rate as being definitively correct. • is a product of the fixed factor share, the mark-up of the technology, and the reciprocal of the electricity price by region. This is a generalized equation, where the subscripts for technology and region are not included. Specifying the fixed factor resource for each backstop and region does not allow for spillovers. For a justification on why this is reasonable see Paltsev et al. (2005b).

The second way in which the fixed factor sets the rate of capacity building is the cost of the fixed factor share in the primary inputs of a technology, as shown in the nesting diagrams above. The share is set at 0.01 for all the advanced energy technologies except for Advanced Nuclear, for which it is 0.001. This is less constraining because more experience with nuclear generation technologies exist, relative to the other advanced technologies. Therefore, constraining capacity building to the same level as completely new backstops would be unrealistic. Further, the values of *a* and *b* are assumed to be the same for all advanced technologies except for two of the technologies. The Advanced Nuclear backstop takes different and less constraining values, for the same reason as those given above. The coefficients also take less constraining values for NGCC without CCS, to reflect the fact that a certain amount of pre-existing knowledge in gas technologies is available, with gas-fired generation constituting a significant share of the conventional fossil technology available in the base year.

The fixed factor governs capacity building of energy technologies in EPPA, and creates an effect similar to learning-by-doing. Therefore since innovation as cost reduction through experience is modeled in EPPA, it is possible to investigate how early investment in CCS affects social welfare under uncertainty.

3.1.3 Modeling CCS investment in EPPA

In EPPA I simulate funds being provided to the Coal with CCS backstop over several years. In the model there is only one representative agent, and so investment in Coal with CCS is subsequently provided by this agent. The investment is modeled as a negative tax, therefore seeming to represent a government subsidy. However it could also be thought of as a generic investment from the private sector, rather than an explicit government-granted subsidy, as consumers could buy shares in publicly traded companies that invest in CCS. Therefore the money provided from the representative agent can be considered as a company investment, or from the government, or some combination of both. More importantly, since there is only one representative agent, the model is unable to distinguish who in society is making the investments.

The CCS investment in EPPA is modeled as a negative endogenous tax. By modeling the investment in this way I am able to specify the dollar amount of the investment, and a negative tax rate is calculated endogenously from that amount, and applied to the Coal with CCS technology.

The tax rate is determined by an auxiliary constraint of the form:

Electricity from Coal with CCS(t) =Investment +Electricity from Coal with CCS without investment(t)

Electricity from Coal with CCS(t) is the electricity generated from Coal with CCS in the USA in a tens of billions of dollars calculated by EPPA, depending on the specifics of the scenario in each particular period. *Investment* is the investment amount specified in each year, also in tens of billions of dollars. *Electricity from Coal with CCS without Investment(t)* is what the electricity output from Coal with CCS *would have been* in that same period if the investment were not provided. In this way, the endogenous tax is calculated such that *Electricity from Coal with CCS(t)* is forced to increase by the investment amount in every period. *Electricity from Coal with CCS without Investment(t)* is calculated by running the scenario without the investment first.[5]

The investment amount in this analysis is $5B in every year from 2015 to 2050 in 1997 dollars. This value is chosen for the investment as it is the same order of magnitude in terms of dollar amount and time scale being discussed in Congress for CCS incentives (Pew Center for Global Climate Change, 2009). The investment is modeled as stopping in 2050, as preliminary simulations without investment show that CCS begins to be economical in 2045 under emissions policies, and so the extra investment would not be needed beyond this point.

By forcing the technology to be built by providing $5B to the Coal with CCS backstop in every year, the capacity is being built up, and the fixed factor endowment increases, lowering the costs towards the n^{th}-of-a-kind costs. The investment therefore speeds up the cost reduction process, in a similar way to learning-by-doing.

[5] *Electricity from Coal with CCS without investment(t)* must be found in each period *t*, by applying the annual investment in every year up until that period, *t-1*. This is necessary as the electricity generated in year *t* will be different if there was investment in CCS before that year, than if an investment were never made.

3.2 Decision analytic framework

Decision analysis is a tool that is used for informing decision making when we face uncertainties. This section explains the decisions analysis model used in this study.

3.2.1 The Decision

This thesis is concerned with how an investment in CCS today can add value to society given uncertainty and a representation of learning-by-doing. Therefore, the decision faced by policy makers and potential investors, is whether or not to invest today, given that we don't know what will happen in the future. The investment would be $5B in every year made directly to the Coal with CCS backstop, beginning in 2015 and lasting until 2050. The decision of whether or not to invest is taken in year 2015, before any of the uncertainties that are described below are resolved.

3.2.2 The Uncertainties

There are several uncertainties that we face that could affect the demand for CCS, and therefore whether investments turn out to be beneficial or costly to society. In this analysis I model three different uncertainties, which are described below.

Uncertainty 1: Stringency of Emissions policy

One uncertainty that could affect how beneficial investment would be is whether there is an emissions policy in the US, and whether it changes to become more stringent or more relaxed, to reflect new information on climate change science or new political priorities. A reasonable hypothesis would be that investing in CCS in a world where we later develop a stricter emissions policy could provide an option value, since learning-by-doing has already taken place and costs are at *n*th-of-a-kind when the technology is demanded. Conversely, if the emissions path gets less stringent, we may have wasted money on investing in a technology where demand will not be as great.

The emissions paths for the scenarios modeled are climate policies that start in 2015, and either get stricter or less stringent in 2030, to reflect changing political preferences. The emissions policies are modeled in EPPA as cap-and-trade policies, and the caps, or emissions paths, are shown in Figure 6. The policies are hereafter referred to as the 'stricter' and 'less stringent' emissions paths, accordingly.

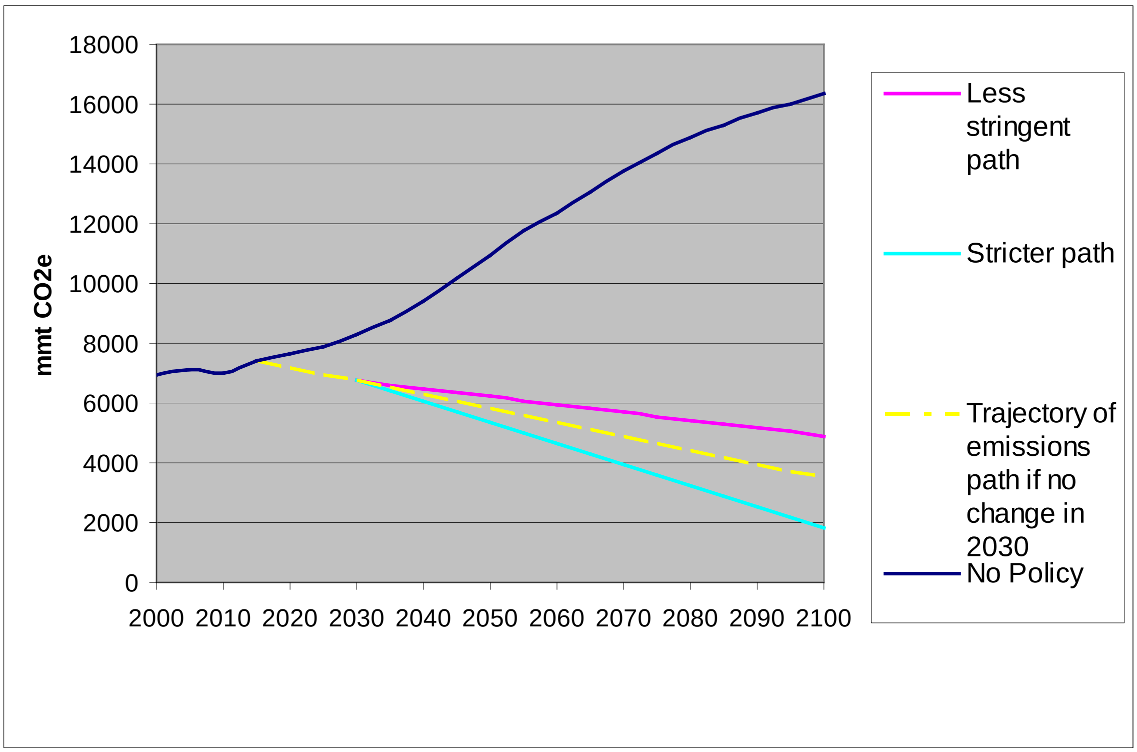

Figure 6. US greenhouse gas emissions for policies in decision tree analysis

The No Policy line on the graph shows the greenhouse gas emissions for the US with no climate policy from 1997 to 2100, in mmt CO_2e. For this study, I model that the US adopts a climate policy corresponding to an emissions path that starts in 2015, shown by the yellow dashed line. If this climate policy were kept in place unchanged until 2100, it would result in a 50% reduction in emissions from 2005 levels.

However, in 2030 I assume that the government wishes to either make this policy stricter or less stringent, due to new knowledge on climate change or evolving political priorities, and so the climate policy either follows the stricter path, or the less stringent path from 2030 to 2050, shown by the light blue and pink lines respectively.

The details of each path are described in the table below.

Table 5. Emissions policy scenarios

Climate policy	Cumulative emissions from 2015 to 2050	Percent below 2005 emissions by 2050	Percent below 2005 emissions by 2100
Trajectory if no change in 2050	238 bmt	18%	50%
Stricter path	233 bmt	25%	75%
Less stringent path	243 bmt	13%	30%

These particular paths are not intended to be indicative of any particular policy in Congress, but are supposed to illustrate how future conditions would affect the outcome of CCS investment by comparing paths that are stricter or less stringent relative to a baseline trajectory beginning in 2015. It is the relative behavior of the emissions trajectory that is important for this analysis, rather than their specific values.

These paths show smaller reductions compared to the climate bills being discussed in Congress. For example, HR2454 specifies an emissions reduction in the range of 68% to 87% below 2005 levels by 2050, depending on the level of offsets adopted (Paltsev et al., 2009). Another example is the 2007 Bingaman-Specter bill which requires 60% reductions below 2006 levels by 2050 (although this bill never made it out of the Senate Environment and Public Works Committee, it is included here to give a scale of the demands of reductions that have recently been discussed in Congress).

Constraints faced by the conditions of the model dictated the choice of reductions represented. The runs in this analysis are carried out until 2100, since it could take a long time before the benefits of investing in CCS could be realized. It is desirable to model emissions paths that reduce greenhouse gasses at a constant rate so that the number of changing factors that could affect the technology mix and welfare change over time is limited, so it is easier to determine whether observed effects are due to the investment and not anything else. If an emissions path of the same reduction rate as the bills mentioned above is applied, and the same constant rate of reduction is continued beyond 2050, which is the year defining the target of these bills, the emissions levels will reach zero before 2100. This may not be a realistic scenario to explore and could result in extremely high carbon prices and welfare costs in the model. Therefore, since a constant rate of emissions reductions is desirable for this study, but zero greenhouse gas emissions are unrealistic, the ramp down of the emission cap is limited.

The emissions paths chosen for this analysis are as strict as possible given this limitation to reflect a same order magnitude reduction as real climate bills discussed on Capitol Hill. However, they are not replicating these bills, and the real bills' inclusion in this discussion is simply to provide context in interpreting the reductions modeled here, which are intended to be illustrative in showing the effects as emissions policies get stricter or less stringent relative to a baseline.

Cost competitiveness of technologies

As explained in section 3.1.1 there are eight energy technologies to switch to from conventional coal. We don't necessarily know which will be most economic and therefore which will take over a significant portion of the electricity market. Investing in a technology that may never become economically competitive could be a waste of money, and so this uncertainty also affects the outcome of the decision.

Adding an uncertainty for the cost of each energy technology in the tree is possible, but since there are eight energy technologies to choose from, this would complicate the decision tree significantly. Therefore, a simpler way of representing cost competitiveness uncertainty would be preferable.

There are constraints that apply to certain energy technologies in EPPA so that they have an upper limit to their capacity. Such constraints exist in the model for electricity from Wind and

Solar, Hydro, and Conventional Nuclear, as explained in section 3.1.1. Very little electricity is produced from Biomass because the land resource is heavily constraining. The backstop technologies that are left to compete to replace conventional fossil generation under a CO_2 emissions policy are Advanced Nuclear, NGCC, NGCC with CCS, and Coal with CCS. Therefore, it is only necessary to explore the uncertainty in cost competitiveness for these technologies in EPPA, as the others have limited expansion possibilities independent of cost.

Uncertainty 2: Size of US gas resource

One way of representing uncertainty in relative cost is to include uncertainty in the magnitude of the gas resource, which would affect the price of electricity from gas. Since the discovery of greater gas resources in the form of shale gas, tight gas and coalbed methane, and new technical improvements in extraction, there could be more proven gas reserves than we previously thought. We could also be over-estimating the gas resource based on these discoveries, and therefore examining a range of gas resource could reflect this uncertainty that would affect cost competiveness of technologies.

For this uncertainty, I have used a lower and upper estimate surrounding the reference gas resource in EPPA, which is of 1650 EJ. These bounds were informed by the forthcoming MIT Future of Natural Gas Study and reported by the US Geological Survey, and are 1100 EJ for the lower bound, and 2200 EJ for the upper bound. (Moniz et al., Forthcoming).

Uncertainty 3: CCS costs

Another way of representing uncertainty in relative costs is accounting for the fact that the n^{th}-of-a-kind costs (modeled as the markup factor) could be higher or lower than current expectations. There is significant uncertainty in the future costs of a technology, especially those that are not currently deployed at commercial scale such as CCS. Many different values are reported on CCS cost, shown for example by Hamilton et al. (2009), Al-Juaied and Whitmore (2009), and the Institute for Energy Research (2010). Although it would be possible to add uncertainties on the costs for all backstop energy technologies that could compete, it is only the relative costs that matter in investigating this particular uncertainty.

A preliminary investigation was carried out to determine the best way to represent costs of technologies as a single uncertainty in the tree, by changing the markups of the different unconstrained energy technologies in EPPA. The results are shown in the Appendix in section 8.1. The finding was that under the emissions policies used for this analysis, Coal with CCS and Advanced Nuclear make up the lion's share of the electricity sector in the latter part of the century. Therefore, adding one uncertainty that reflected a world where CCS was more economic than Advanced Nuclear, and vice versa, would represent uncertainty over the competitiveness of the technologies. Since it is only the relative costs of technologies that matter in terms of which gains market share, a range of CCS markups surrounding the original markup was found such that when the mark up was varied within this range, while holding the Advanced Nuclear mark up constant, the same technology mix and welfare output resulted as from holding the CCS markup constant while varying the Advanced Nuclear markup.

Since only these two technologies are competing in the latter part of the century, having one uncertainty for just the CCS markup, rather than for CCS *and* Advanced Nuclear, is sufficient to recreate the uncertainty for cost competitiveness as only relative costs matter.

The mark up for the Advanced Nuclear backstop is not calculated using the same LCOE calculation and EIA inputs as all the other technologies, as it is very difficult to estimate the costs of nuclear in the future as we do not know which particular technology we will adopt, and because it is modeled through two backstops in EPPA. For examples, Du and Parsons (2009) estimate the capital cost at 4000 $/kW, and the EIA (2009b) estimates only 3318 $/kW. Therefore, rather than using the markup from Morris et al. (Forthcoming), the Advanced Nuclear markup was determined from the same preliminary analysis to calculate a range for CCS markups as an uncertainty. For more details see appendix section 8.1.

The uncertainty in the decision analysis should result in scenarios where Coal with CCS takes a large market share over Advanced Nuclear, and vice versa at the extreme upper and lower bounds. Therefore, through the preliminary investigation, a reasonable range of markups for CCS was found to be 1.4 for the lower bound, and 1.6 for the upper bound. A markup of 1.85 was determined appropriate for the Advanced Nuclear backstop to ensure representation of scenarios where CCS or Advanced Nuclear is more competitive at the lower and upper CCS markup bounds respectively.

3.2.3 Decision tree

A model in the form of a decision tree can be constructed to represent the early investment decision problem. The decision of whether to invest in CCS or not is made before the uncertainties are resolved, in 2015.

The decision tree with these uncertainties described above is shown in Figure 7.

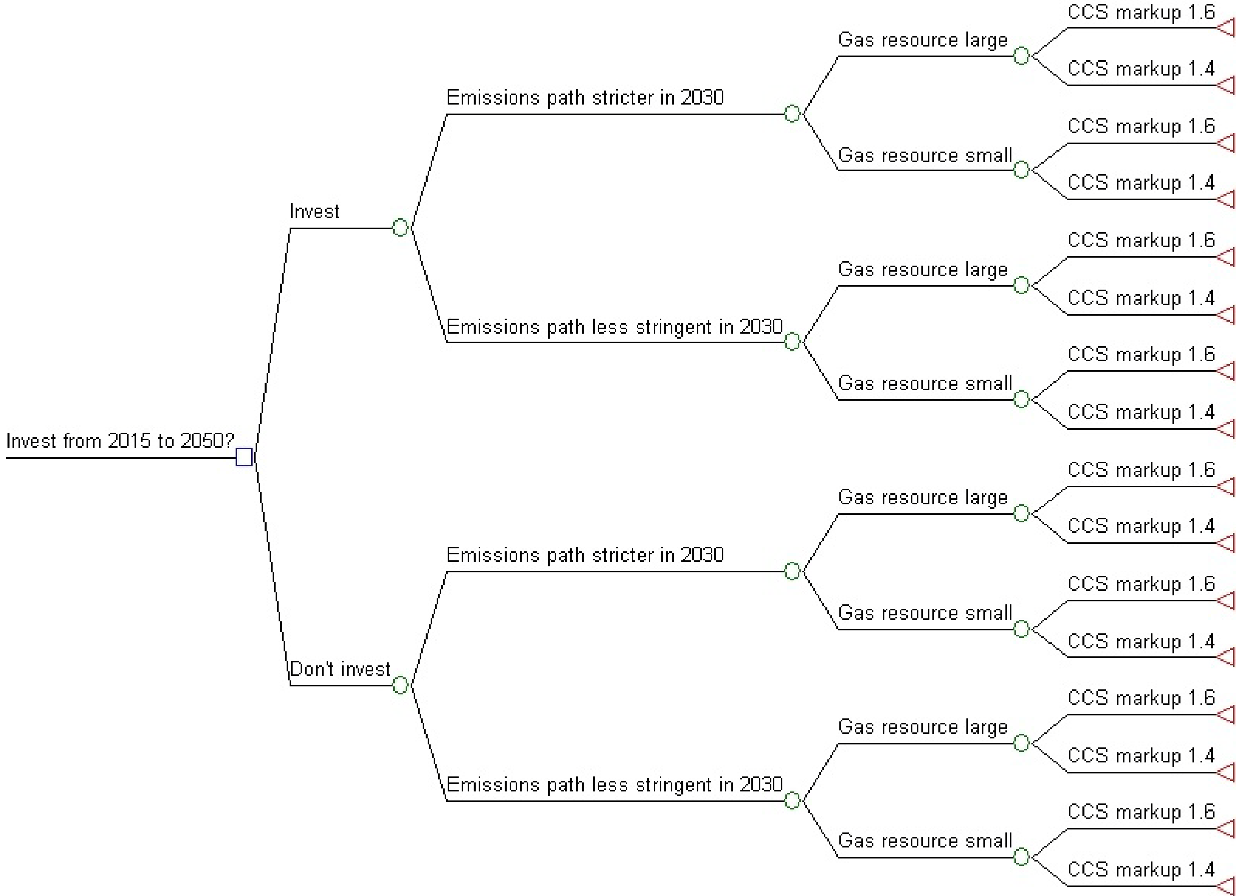

Figure 7. Decision tree model for analysis

3.3 Combining EPPA and decision analysis

Each branch of the tree specifies a set of assumptions and a scenario that is run in EPPA. Every run gives a result of a measure of the welfare in every year, given the assumptions applied. The welfare metric is a dollar value measure of equivalent variation and represents a change in aggregate market consumption and leisure activity (Morris, 2009). The economic theory behind this assumption is that workers can choose whether to work or not, and they value their non-work time at the marginal wage rate. For more information see Morris (2009).

A net present value is calculated for the welfare outputs in each period of the model using a 4% discount rate. The discount rate used is 4% because this is typically the rate used when representing borrowing and banking of permits across periods in EPPA within the MIT joint Program on the Science and Policy of Global Change (see Jacoby et al., 2006 for an example). The correct choice of discount rate is part of long-established debate with differing opinions regarding intergenerational equity and financial valuations. This discussion however is beyond the scope of this study, and for consistency with the EPPA modeling literature a 4% discount rate is chosen. Section 4.1 shows a sensitivity test on the discount rate, to demonstrate how different choices of rate can affect benefits from CCS investment. The discounted NPV of the welfare for a one of the scenarios can be compared against the NPV of the welfare in the No Policy case. The difference between the two is the cost of the policy in dollars. In order to be able to judge relative costs of policies across many scenarios, the percentage change in NPV of welfare from the No Policy case is used as the output measure for each branch of the decision tree, as for the purposes of comparison it is easier to compare these small percentage differences rather than large dollar sums. The percentage difference in NPV from the NPV in the No Policy case is the metric for comparing which branch is optimal given that we wish to meet our emissions target at the lowest welfare cost possible.

Rather than rely on specific assumed probabilities for all the uncertainty branches and solving the decision tree once, I carry out sensitivity analyses spanning the range of all possible probability combinations that could be assumed. Specifically, once the percentage change in NPV of welfare for each branch of the tree is determined, I perform a sensitivity analysis on the probabilities of each uncertainty by ranging them from 0 to 1 and solving the tree at every increment to find the threshold value at which the optimal decision changes[6]. In this way, I am

[6] This analysis solves the tree by calculating expected values, as explained in section 8.3 in the appendix. It is important to recognize however that if expected value is the metric by which the optimal decision is reached, this assumes that this decision will be taken multiple times and that on average the outcome will equal the expected value. If the decision is only to be taken once, then risk preferences of the individual should be taken into account, as outcomes will not necessarily follow what is dictated by probability in any given individual instance. Risk preferences are not taken account here as the purpose of the thesis is to introduce a new framework, the overall method for which would be largely unchanged when preferences are accounted for. Taking account of risk preferences would however be a useful extension of this study and should be considered when extending this framework to informing policymakers' decisions about energy technology investments.

able to determine under which conditions the optimal decision is to undertake early investment, and under which conditions it is best not to. If policy makers are able to make their own educated assumptions about the range of probabilities that they believe to be the case, they may find the relevant decision of whether or not to invest within the results presented. More importantly, investment decisions that are robust over a wide range of assumptions can be identified by this method, and extended beyond investments only in CCS.

4 Results

This chapter presents the results of the analysis. In order to understand how investment in coal technologies with CCS can affect welfare the results for some illustrative scenarios simulated deterministically are presented to demonstrate the intertemporal welfare effects of early investments. These scenarios provide the motivation for extending the investigation to perform a decision analysis. The next section presents the results from the decision analytic framework, first in the form of sensitivity analysis for one uncertainty (specifically the stringency of emissions policy), followed by sensitivity analyses that vary two of the three uncertainties (stringency of emissions policy, size of gas resource, and CCS costs) simultaneously.

4.1 Deterministic scenario analysis of early investment in CCS

I begin by examining what happens to societal welfare if an investment in CCS is made in a deterministic world with no uncertainties. An investment in any of the advanced energy technologies would alter the technology mix within the electricity sector. This in turn will affect societal welfare, the metric by which we may judge the cost-effectiveness of meeting any emissions policy that is implemented. Therefore, examining the technology mixes that result with and without an early investment in CCS is necessary to understand the welfare effects of the investment.

Before comparing a case with and without CCS investment, the No Policy case must be run first, this is the baseline used to calculate the cost of any policy that could be implemented. The technology mix for the No Policy scenario is shown in Figure 8. EPPA does not model the benefits of GHG mitigation, only the cost of a policy such as cap-and-trade. Therefore, all scenarios with emissions policies, whether CCS investment is included or not, will be more costly than the No Policy case. The welfares for each scenario are discounted to give a net present value, and the cost of the policy is measured as the difference in NPV of welfare from the policy and No Policy case. In order to compare the costs of multiple policies, rather than comparing absolute values, the percentage difference in NPVs of welfare can be used to compare across the different scenarios to determine which is the cheapest to society.

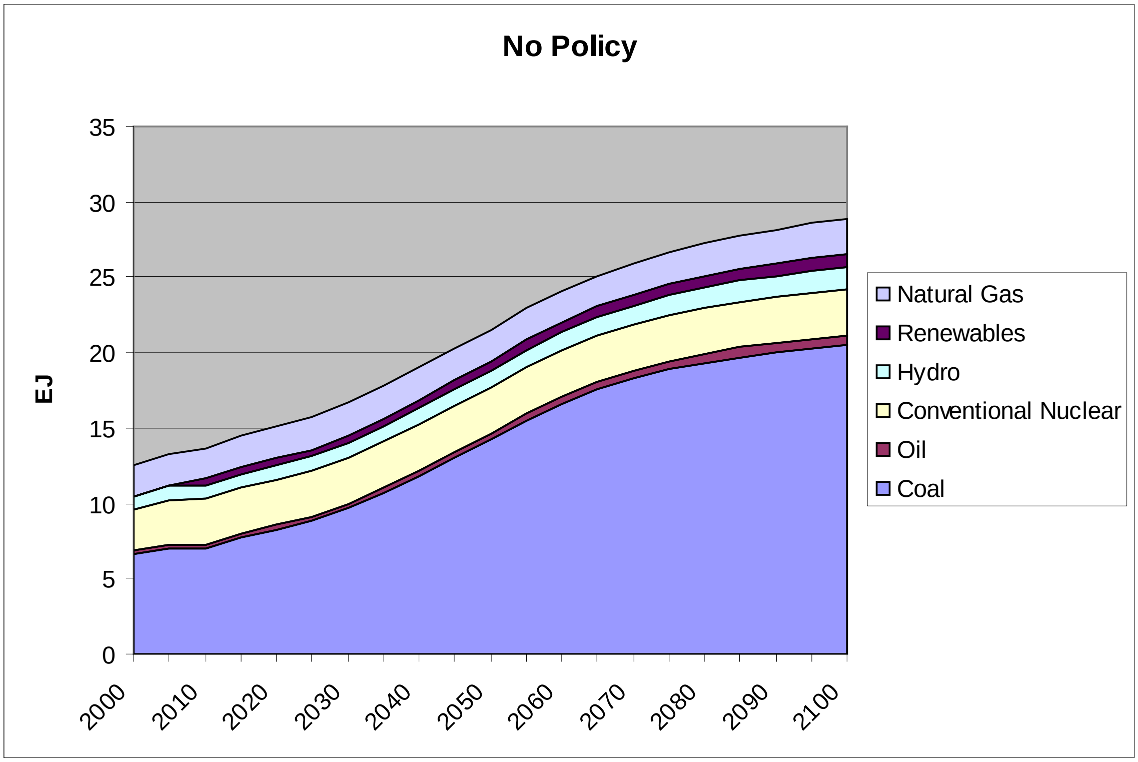

Figure 8. US Electricity mix, no policy scenario

Figure 8 shows the electricity generated, by each technology, in exajoules (10^{18} joules). It should be noted that this is the electricity generated, not the installed capacity. Under the No Policy scenario, the total electricity production increases over the century. This is because there are no constraints on the energy sector, and as the economy grows over time, the electric power sector can grow to accommodate the increasing demand. Coal and oil in the graph are from the conventional fossil backstop, shown in Figure 1. The Renewables contribution in the graph is the sum of electricity from the Wind and Solar backstop and from the Biomass backstop. The natural gas contribution is the total electricity generated from gas, being the sum of electricity from gas in the conventional fossil technology and the electricity from the natural gas combined cycle (NGCC) advanced technology. Almost all of the increase in electricity generation is from coal, and the contribution from each of the other technologies generally remains unchanged over the century. This is expected because of the constraints on Renewables, Hydro and Conventional Nuclear (see section 3.1.1). Gas is higher cost compared with coal, which is why the extra demand is filled by coal rather than gas. There is no electricity generated from the Advanced

Nuclear technology, NGCC with CCS, or Coal with CCS. This is because coal-fired power is much cheaper compared to these technologies, as it is not penalized for emitting CO_2.

If a GHG emissions cap is imposed, the resulting technology mix is different (Figure 9). The policy applied here consists of declining emissions to a target of 75% reduction below 2005 levels by 2100. This is the 'stricter' emissions policy as explained in section 3.2.2. The policy comes into force in 2015, and the cap becomes tighter in 2030, with a constant rate of reduction in the cap thereafter. The CCS markup is assumed to be 1.54 (Table 3), and the total gas resource is 1650 EJ (Section 3.2.2). This represents a reference case of assumptions, to illustrate how CCS investments can typically affect the technology mixes and welfare in EPPA under an emissions constraint.

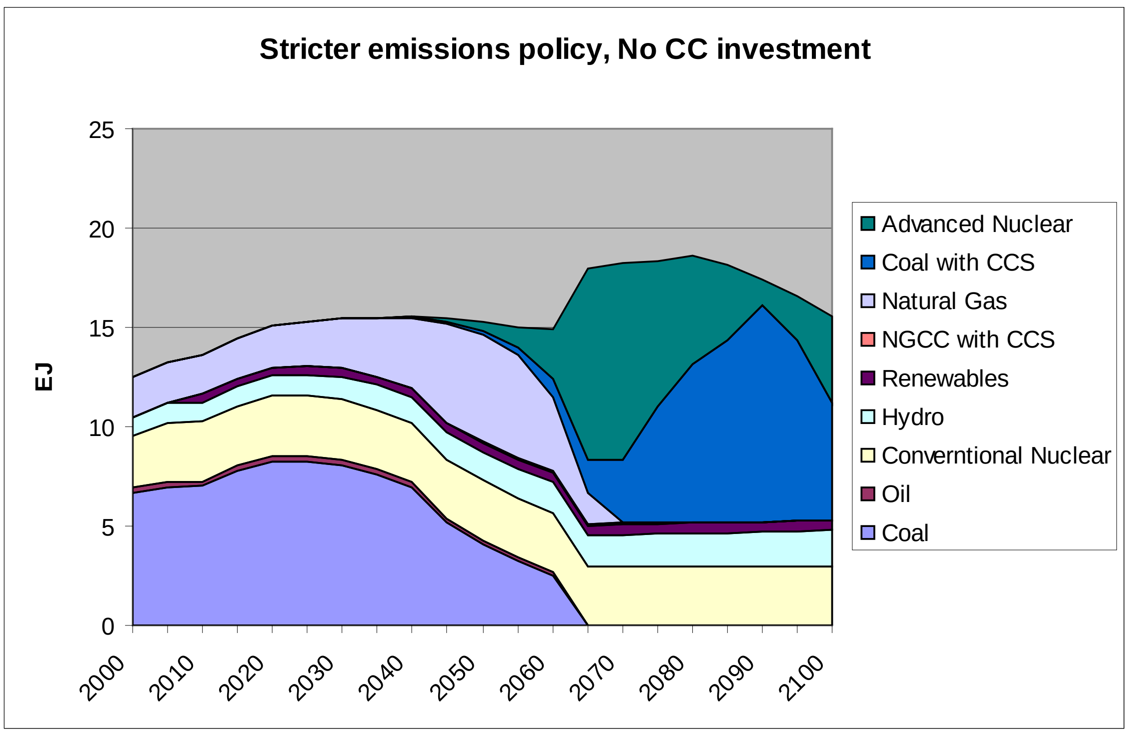

Figure 9. US Electricity mix, with emissions policy

There are several differences of note in the technology mix under a policy as compared with that under the No Policy scenario. The first difference is that generation from conventional coal is phased out of the electricity market in this case. This is because coal-fired generation becomes much more expensive due to its emissions and the rising price of carbon permits. Eventually it becomes more expensive than cleaner alternatives, and in this scenario, Advanced Nuclear and Coal with CCS begin to enter the electricity mix in 2045, around the time that conventional coal begins to be pushed out.

The second point is that electricity consumption does not increase uniformly over time as it does in the No Policy case. Figure 9 shows a dip in overall electricity consumption between 2045 and 2070. This drop in consumption represents a period of time when coal, the conventional energy source, is expensive and cleaner alternatives are still too expensive to be used at scale. The cheapest way of meeting the emissions target at this point is to reduce total electricity consumption, because coal is expensive and there is nothing else that is cheaper. This is why there is no smooth increase in electricity generation. Consumption will then rise quickly once cleaner technologies, such as Advanced Nuclear and Coal with CCS become economical as the CO_2 permit price rises, and learning-by-doing occurs. This is shown in the results with the steep increase in electricity use in 2065, as the fixed factors are reduced as Advanced Nuclear and Coal with CCS generate more and more electricity and their costs reduce accordingly to n^{th}-of-a-kind costs. Production from NGCC with CCS is negligible because it is the most costly of the technologies. Hereafter Coal with CCS is referred to as ‘CCS’, since NGCC with CCS plays a limited role in the technology mix due to its high cost and will not be discussed further in the analysis below.

Under this GHG policy scenario there is a gradual reduction in electricity consumption towards the very end of the century. This is due to the fact that the emissions cap continues to decrease, and a significant proportion of the energy mix is from CCS. CCS still emits some CO_2 as the capture rate is not quite 100%. Since nuclear energy has no CO_2 emissions, the price of electricity from CCS rises above that of Advanced Nuclear in 2090, due to the increasing carbon price, causing Advanced Nuclear to increase its share of generation. This is why CCS consumption drops and Advanced Nuclear fills the gap. However, Advanced Nuclear is still expensive, and so overall it is cheaper to continue to reduce total electricity consumption while switching from CCS to Advanced Nuclear, which is why the decline in electricity continues as CCS use drops.

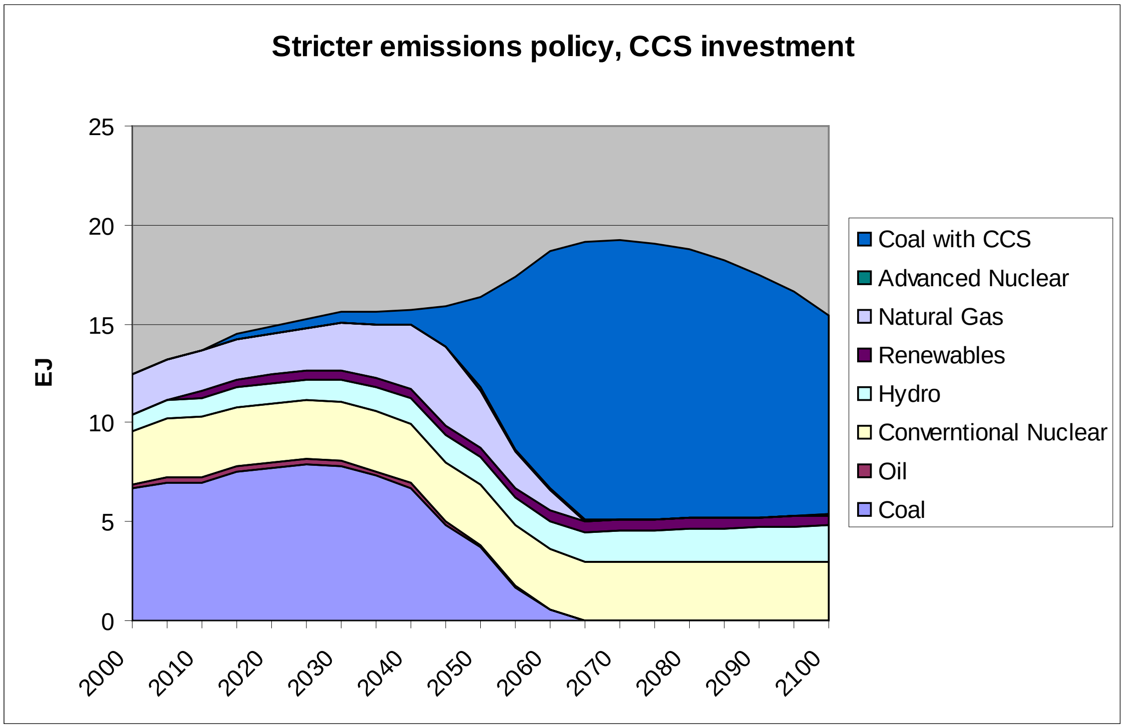

Figure 10. US electricity mix, with emissions policy and CCS investment

Now assume that an early investment is made in CCS of $5 billion per year between 2015 and 2050, under the same GHG emissions policy shown above. This will result in yet a different mix of technologies to produce electricity (Figure 10). As in the case without early investment, conventional coal (without capture) is pushed out of the electricity market. This is a result of the overall emissions policy, and not the CCS investment.

However, in the early investment case, electricity from Advanced Nuclear is almost entirely replaced by CCS. This lock-out occurs because CCS is utilized far earlier, from 2015, as opposed to 2045 in the no investment case. The earlier production, even on a small scale, accelerates the learning-by-doing process so that by 2045 the technology could be built at nt^{h}-of-a-kind costs. Therefore when carbon prices become high enough for low carbon technologies to be competitive and start to enter the market in 2045, CCS can be expanded far more rapidly than Advanced Nuclear can. In addition, the early investment allows electricity consumption to increase gradually throughout the 2040-2060 timeframe. This is because, in contrast to a situation where there are no early investments in CCS, CCS is now available at n^{th}-of-a-kind costs as an alternative to coal, and so the emissions target can be met by using CCS rather than just reducing electricity consumption altogether.

Under the same emissions policy, early investment in CCS changes the technology mix in important ways. We can better understand how the penetration rate of CCS in the market is affected by investments by examining the electricity from CCS in isolation. Figure 11 shows the electricity consumption in EJ only for CCS, for the cases with and without early investment.

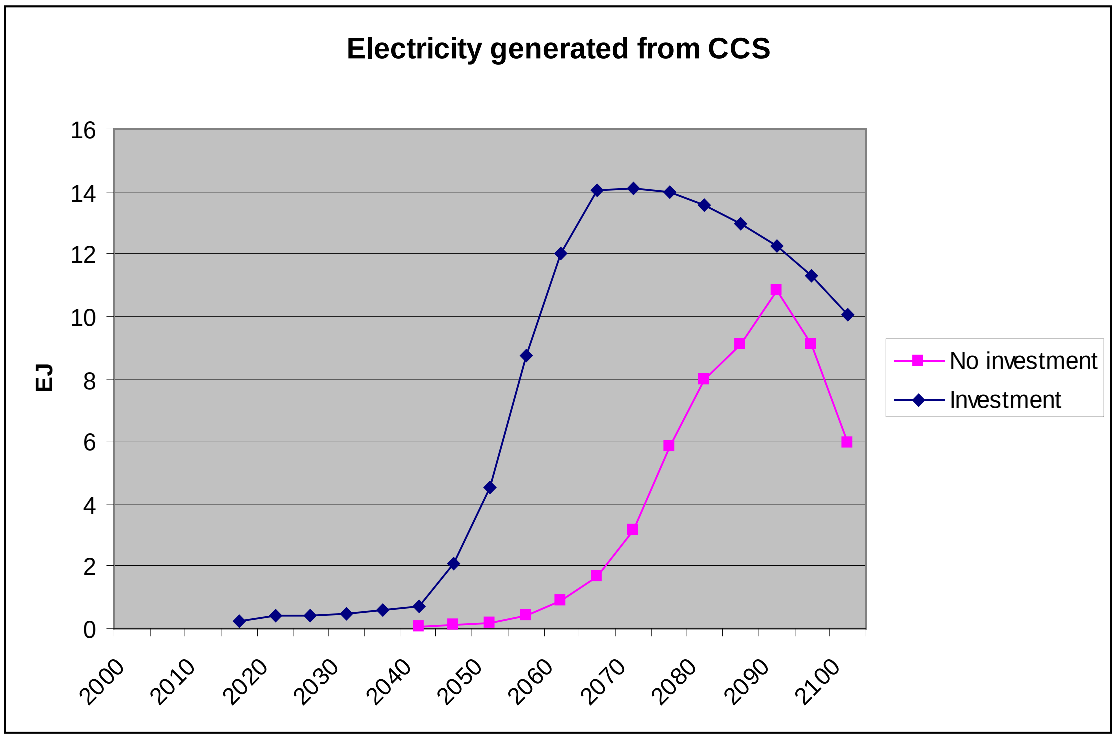

Figure 11. Electricity from CCS

When there is early investment electricity generated from CCS will begin in 2015, when the investment starts. The electricity output due to the investment is almost constant until 2045. This is because a fixed dollar amount of $5B is being provided for CCS technology in every year, and therefore only $5B worth of electricity from CCS is produced in every year. However, the electricity consumption from CCS rises very slightly between 2015 and 2045 because learning is occurring and costs reducing, and so more electricity can be generated for $5B. By 2045 the carbon price has become high enough for CCS to be cost-competitive. If there has been no investment in CCS, the technology will begin to generate electricity in 2045, and will expand slowly over time since no capacity has been developed to construct CCS at large scale and no cost reductions have occurred. However when investments are made, from 2045 onwards the penetration rate is much greater as the learning has already occurred and so the technology can be built out without significant constraint.

In Figure 11, the gradual decline at the end of the century for the scenario with investment is due to the same reason for the decline in total electricity consumption - CCS makes up most of the electricity mix, but the technology still emits some CO_2 (assuming near 90% capture rates), and with an ever-decreasing GHG cap in place becomes more costly over time. The steeper drop in the other scenario is due to the same reason, but is sharper because Advanced Nuclear is available, which replaces CCS.

While the early investment in CCS builds capacity and results in the ability to build at lower cost in the second half of the century, this comes at a cost earlier in the century since we are intentionally forcing production of a higher cost technology. It is therefore important to compare the intertemporal pattern of welfare over time to understand the net effect, and whether overall this investment is beneficial to society. Because all policy cases are more costly to society than the No Policy case, the percentage difference in welfare of a policy case from The No Policy case is always negative. The greater the percentage difference of welfare in absolute terms from The No Policy case, the lower the societal welfare, and the more costly the policy becomes.

Figure 12 shows the percentage change in welfare from the No Policy case, for each of the scenarios for the stricter emissions path. The graph is calculated by taking the percentage difference of the welfare in every year from the No Policy case, and is undiscounted.

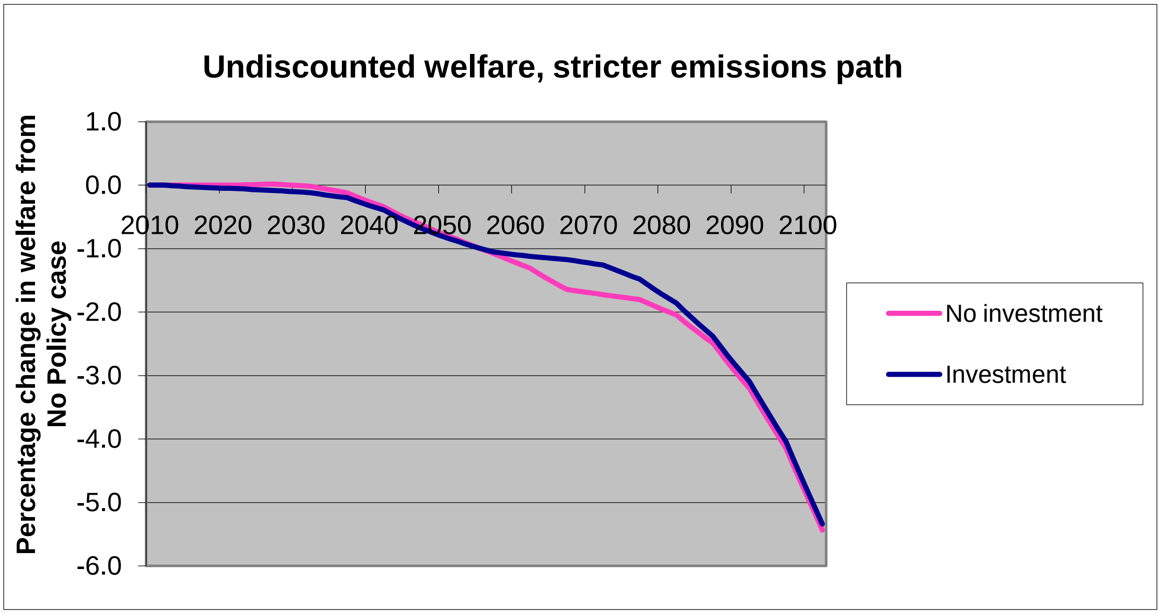

Figure 12. Graph of welfare comparison, stricter policy

As expected, in the early part of the century the percentage change in welfare is larger in absolute terms for the CCS investment scenario, as compared with the no investment case. In other words, at the beginning of the century, investing in CCS is a more costly action than not investing.

However, beginning in approximately 2055, after CCS starts become economical under this emissions cap (2045 as shown in Figure 11) the scenario without CCS investment becomes more costly. This is because CCS demand increases later in the century as the emissions caps get tighter, and in the investment case learning has occurred and CCS is cheap to build out quickly. Therefore since society is able to consume electricity from CCS and meet the emissions targets more cheaply than reducing overall consumption, there is a gain in welfare over the no investment case towards the end of the century.

By the end of the century, the cost of the meeting the emissions policy is the same, whether there was investment in CCS or not. This is because by that time, all the learning has occurred, i.e., the fixed factor is no longer constraining for both cases, and the CCS investment no longer affects welfare.

These results demonstrate that under this particular emissions policy, early in the century a decision today to invest increases welfare loss, but later in the century it actually decreases welfare loss. It is possible to calculate a net present value of the welfare to provide a definitive comparison between the two scenarios – the case with investment, and the case without. Table 6 shows the NPVs for the No Policy case, and the two scenarios, discounted at 4%.[7] The table shows that, as expected, the NPV of welfare is higher in the No Policy case, since EPPA does not take account of the benefits of GHG emissions mitigation. For this emissions policy, the welfare is higher when there is an investment in CCS, than when there is not, by $1.33 trillion, which is the benefit of the CCS investment. Another way of representing the benefit of the investment is to calculate the percentage change in the NPV of the welfare from the No Policy case. In contrast to the graph in Figure 12, only the NPVs are compared by a percentage difference, not the welfare in every year. The results show that, as expected, the percentage changes are negative for both cases, since welfare is worse under a policy scenario. Further, the benefit, which again is the difference between the percentage change in NPVs, is positive, demonstrating that under this GHG policy investing in CCS in this scenario is improves welfare.

Table 6. Benefits of CCS investment under stricter emissions policy

	NPV of welfare 2005-2100 discounted at 4% (Trillions of $)	Percentage change in NPV of welfare from No Policy NPV of welfare
No Policy	3797.03	-
No investment	3741.77	-1.455
Investment	3743.10	-1.420
Benefit of investment	1.33	0.035

Therefore, in this deterministic scenario, given the choice of whether to invest in CCS or not today, we should choose to invest. In other words, the up-front investment cost is more than compensated by the cost savings later when CCS is needed at a large scale.

[7] See section 3.3 for an explanation as to why a discount rate of 4% is used.

This analysis assumes a 4% discount rate. The result however could be different should an alternative discount rate be assumed.

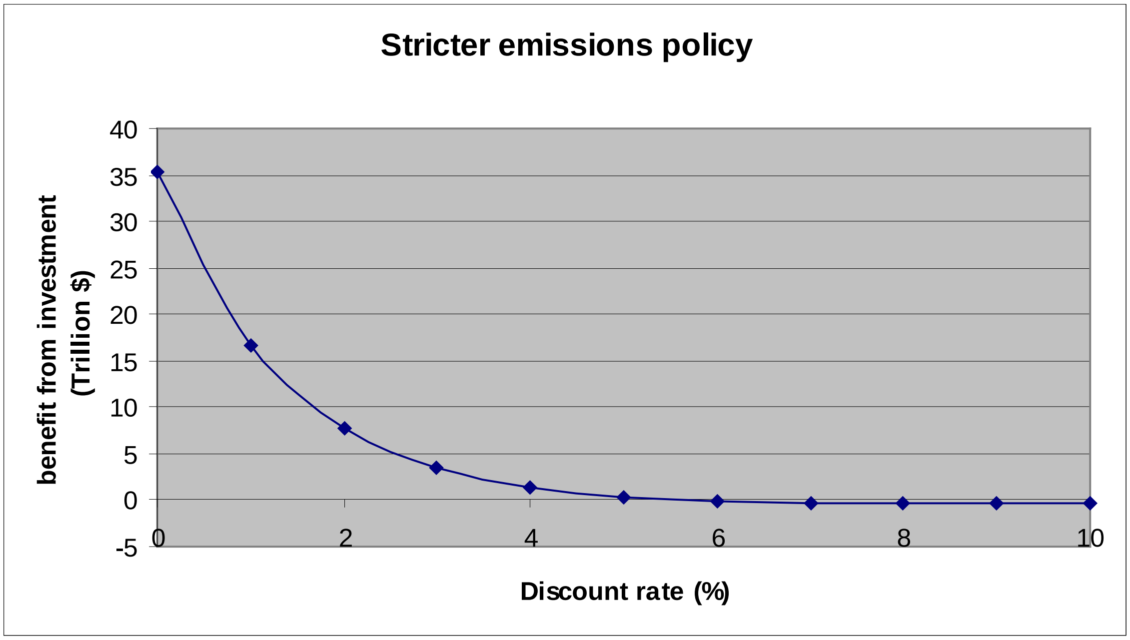

Figure 13. Sensitivity test of discount rate on investment benefit for stricter policy

Figure 13 shows how the benefit of investment in CCS in trillions of dollars changes with the discount rate. Since most of the benefits of the investment are seen later in the century, the lower the discount rate, the greater the benefits as they are discounted less and worth more. At a discount rate of 0%, the benefit from the investment is the difference in welfare summed over every year, providing the upper bound to the gains from investment.

Once the discount rate increases above 6% the overall benefits become negative as the upfront cost of the investment outweighs the heavily discounted benefits that occur later. However, as the discount rate gets higher, the now negative benefits, i.e. costs, do not increase further. This is because the costs of the early investment are also discounted more heavily, and so the higher the discount rate, the closer the NPVs of the welfares for the two policies become, which leads to an upward trend towards $0 benefit.

Therefore, the result that investing in CCS under this policy is the better option holds only if the discount rate one uses is less than 6%. Beyond 6%, investing becomes the more expensive choice, although the cost of choosing to invest does not increase substantially as the discount rate increases as it is bounded by the investment amount, and eventually tends to $0.

If there is a different emissions policy, the comparison of investment decisions may lead to different results than those for the policy shown above. This can be tested by repeating the above exercise for the 'less stringent' emissions path described in section 3.2.2, where the emissions decline at a slower rate after 2030 ending with a 30% emissions reduction below 2005 levels by 2100, instead of 75%. The percentage change in welfares with and without CCS investment under this emissions policy are shown in Figure 14.

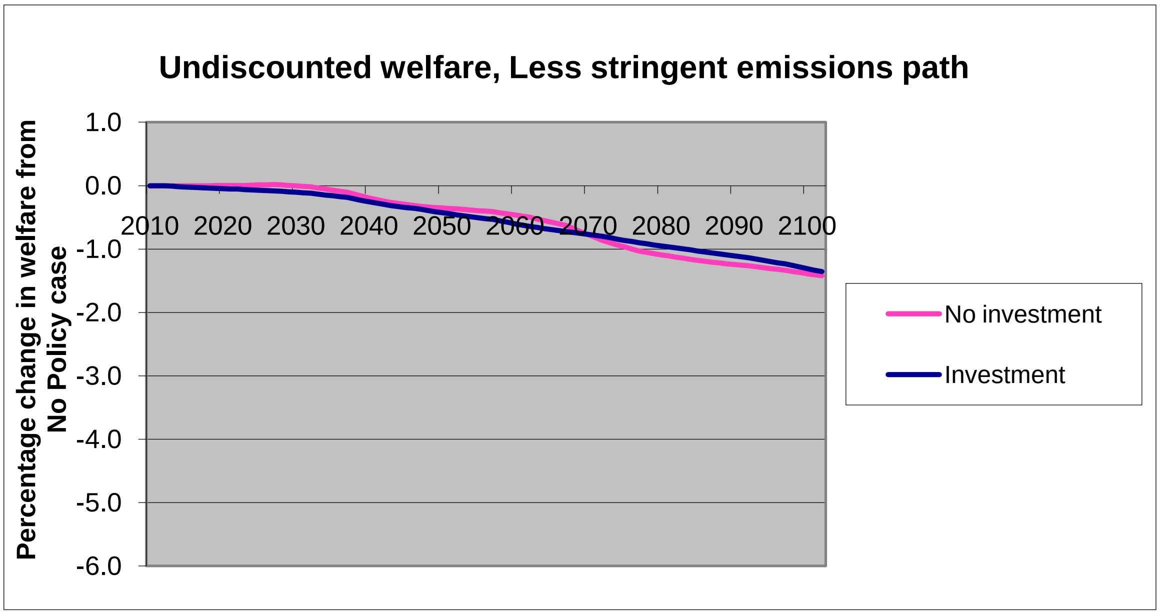

Figure 14. Graph of welfare, comparison under less stringent policy

Under the less stringent policy, the loss in welfare is smaller than under the stricter case with or without the investment in CCS, since the amount of total emissions reductions is not as great. This is because we can meet the less stringent emissions policies with less effort, and so economically social welfare is better than if a stricter policy were applied, since only costs of climate policies and not benefits are accounted for. As above, the scenario with investment results in greater welfare losses early in the century, and the no investment scenario has greater losses toward the end of the century. However the point at which the no investment case becomes more costly occurs in 2075, later than under the stringent policy, demonstrating that the benefits of investing in CCS appear much later under this emissions policy. This is because emissions do not decline as rapidly, and therefore the carbon price rises more slowly and it takes longer for CCS to be economical. Further, since the curves are closer together towards the end of the century, the benefits of investment seen in the later years are not as great as in the stricter policy case.

Table 7 gives the values for NPV of welfare and the percentage change in NPV of welfare for the less stringent policy.[8]

Table 7. Benefits of CCS investment under less stringent emissions policy

	NPV of welfare 2005-2100 discounted at 4% (Trillions of $)	Percentage change in NPV of welfare from No Policy case
No Policy	3797.03	-
No investment	3758.26	-1.021
Investment	3756.80	-1.059
Benefit of investment	-1.45	-0.038

The table shows that the benefit to investment when the welfare is discounted at 4% is negative. This means that investment under this policy is worse than not investing. Carrying out the same sensitivity on discount rate yields the following result:

[8] The technology mixes for the cases with and without investment for the less stringent path are included in appendix section 8.2.

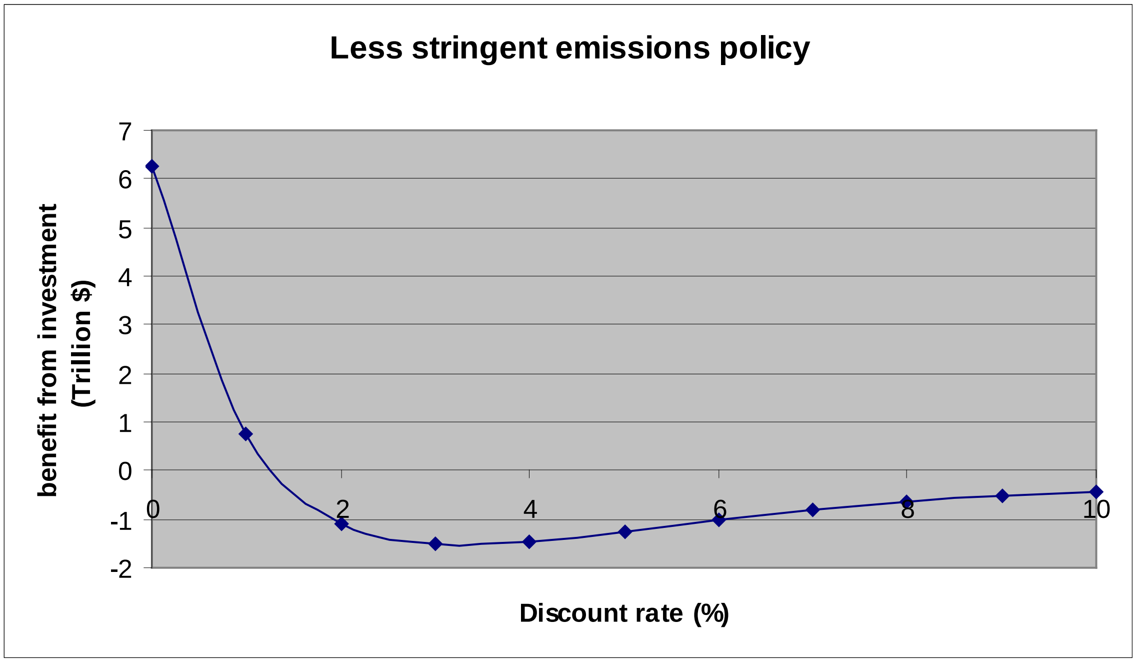

Figure 15. Sensitivity test of discount rate on investment benefit for less stringent policy

The results of the sensitivity show that if the discount rate used is lower than approximately 1.5%, then CCS investment in this case is beneficial. This is expected, as the benefits from the investment are smaller, and later than for the stricter case, and so the discount rate must be very small in order for the benefits to outweigh the annual $5B payment to CCS. Similarly to the results for the stricter emissions policy, as the discount rate increases, the investment becomes costly, but reaches a lower limit and then tends to $0, as the costs of the investment are discounted more and the NPVs tend to the same value.

This section demonstrates that there are indeed situations where it is beneficial to invest in CCS, under the particular assumptions made for a given deterministic scenario. If we can decide on a discount rate, then for each policy we know whether it is better to invest or not. However, in reality the emissions policy in the future is uncertain, and so it is not clear which decision potential investors should make today. Further, there are other uncertainties beyond just the emissions policy that could affect whether investment is the better option. These initial scenarios provide the motivation to create a decision model to help answer the question of CCS investment, given that we do not live in a deterministic world and do not know which assumptions about the future will necessarily become true. If, under uncertainty, it transpires that there are still situations where investment with CCS is more beneficial to society than not investing, then there is an option value to early investments in CCS in those cases.

4.2 Early investment in CCS under uncertainty

For the decision analysis, sixteen runs are carried out in EPPA with the assumptions specified by the uncertainties described in the methodology chapter. These different scenarios are combined to form a decision tree. Each run corresponds to a branch of the tree and the percentage change in the NPV of welfare from the No Policy case discounted at 4%, (analogous to the values in the far right columns of Table 6 and Table 7) are the outputs for each branch (see Figure 16).

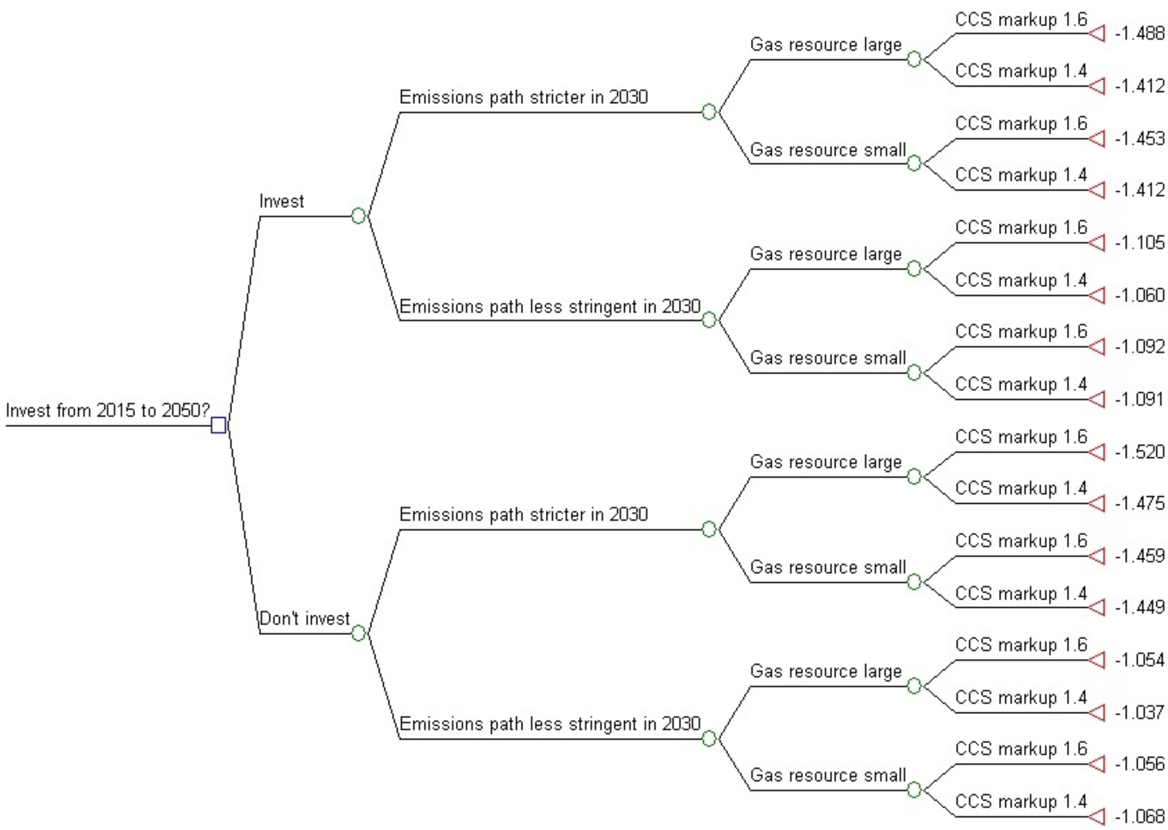

Figure 16. Decision tree with percentage change in NPV from No Policy NPV as outputs

As explained in section 3.2.2, the large gas resource corresponds to 2200 EJ, and the small resource to 1100 EJ of reserves in the USA.

Rather than show the optimal decision for a given assumption for the probabilities on each uncertainty node, sensitivity analyses are performed. This approach identifies the conditions under which it is optimal to invest in CCS and when it is not. This provides a range of probabilities for each of the uncertainties for which CCS investment is the right, or wrong decision.

4.2.1 One-way sensitivity test

Section 4.1 showed that under the stricter emissions policy using a discount rate of 4%, CCS investment had a smaller welfare loss than no investment, but under the less stringent policy it did not. Therefore, I carry out a one-way sensitivity on the future GHG policy uncertainty, while holding constant the probabilities of future CCS cost and natural gas resource supply. The probability of the emissions path becoming stricter in 2030 is varied from zero to one[9]. For each value of this probability, the decision model is solved to find the optimal decision. For this test, the probabilities of the other uncertainties are assumed to be 0.5. For a detailed explanation as to how this graph is constructed see section 8.3 in the appendix.

[9] It is important to remember that the emissions path only gets stricter or less stringent, and the probabilities must add to 1. Therefore a 90% chance the path becomes stricter, is equivalent to a 10% chance it will get less stringent.

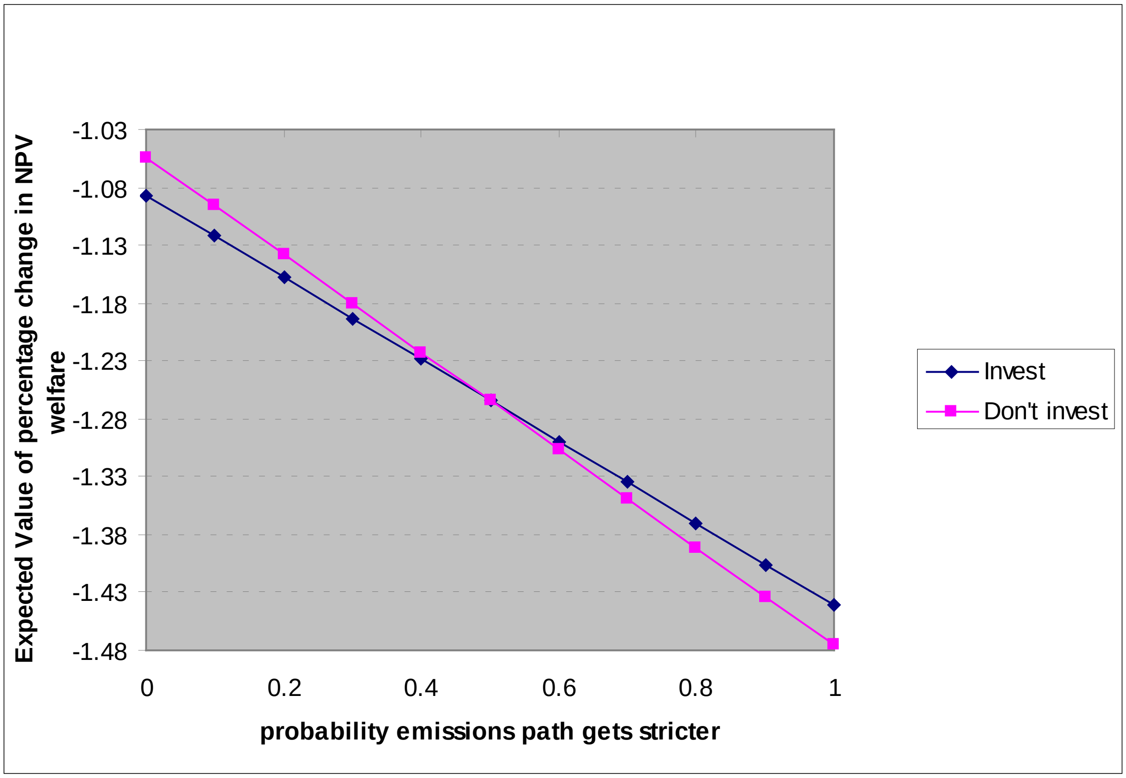

Figure 17. One-way sensitivity on emissions path stringency. Probability of large gas resource and CCS mark-up of 1.6 both held constant at 0.5.

Figure 17 shows the results of the sensitivity analysis. The vertical axis shows the expected value of the percentage change in NPV of welfare from the No Policy case. The optimal decision is defined as the decision giving the outcome that minimizes the percentage difference in NPV of welfare change in absolute terms. Because all the values are negative, the higher the point on the graph, the smaller the welfare loss, and the better the policy. If the probability of more stringent policy is between 0 and 0.5, the decision not to invest in CCS gives the better result. If the probability is between 0.5 and 1, the decision to invest in CCS gives the better result. Therefore, for this specific CCS cost and gas resource, if we believe there is greater than a 50% chance the emissions policy will get stricter, we should invest in CCS; otherwise we should not invest.

If the probability of the emissions path getting stricter is less than 50%, there is an option value to investing in CCS since there is a benefit to investing, and the expected value of making early investments in CCS is the difference in the expected percentage difference in NPVs of welfare, multiplied by the NPV of welfare of the No Policy case. For example, if the probability of the emissions path getting stricter is 1, the difference in expected values is:

$$(-)\ 1.44 - (-)\ 1.48 = 0.04$$

where -1.44 and -1.48 are the values taken from the graph at a probability of 1. The expected value of investing is therefore 0.04% of the NPV of the No Policy case, which is $3797.03 trillion (Table 6). Therefore, if we are certain that the emissions path will get stricter (probability of 1) then the expected value of investing in CCS today is $1.5 trillion.

This expected value decreases as the probability decreases, and eventually becomes negative below a probability of 50%. Figure 18 shows how the expected value of investing changes as the likelihood of a stricter emissions path varies.

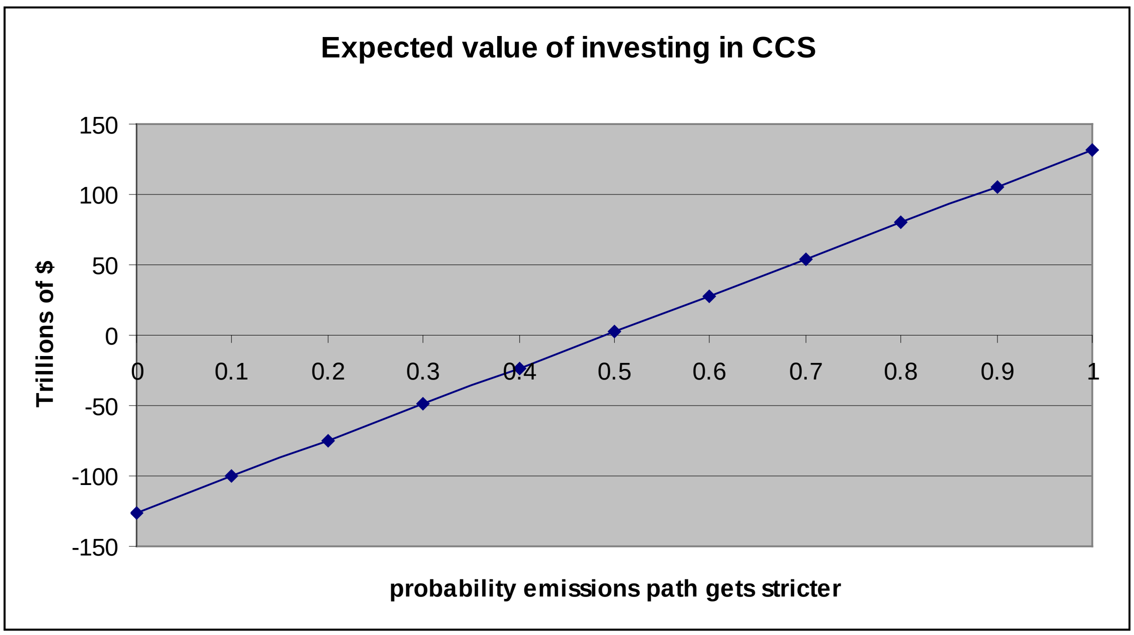

Figure 18. Expected value of investment in CCS as a function of probability of emissions path

These results are consistent with those of the deterministic scenario analysis above. The intuition is that we should not invest heavily in a technology that we will not need to build out quickly, which would be the case if the policy turns out to be less stringent. However, these results alone are not sufficient in informing whether our society would benefit from investments in CCS, as this analysis holds two of the uncertainties constant, when in fact we are not certain of their likelihoods. Therefore a higher dimensional sensitivity analysis, where multiple probabilities are varied is required.

4.2.2 Two-Way Sensitivity Analysis

Because there are three uncertainties, a three-way sensitivity would show what the optimal decision is under all conditions possible in the tree. Rather than performing a three-way sensitivity test, which would give rise to a 3-dimensional probability space, which is often visually difficult to interpret, I perform a two-way sensitivity test for the three combinations of uncertainty pairs while holding the third uncertainty constant. The third uncertainty is held constant first at a probability of 0.1 while the sensitivity is carried out, and then the process is repeated while it is held constant again at 0.9, to show upper and lower cross-sections of the 3-D probability space.[10] This will show trends in the surfaces of the 3-D shape and is sufficient for drawing conclusions about conditions where investment is the right or wrong choice.

Probability gas resource is large is 0.1 **Probability gas resource is large is 0.9**

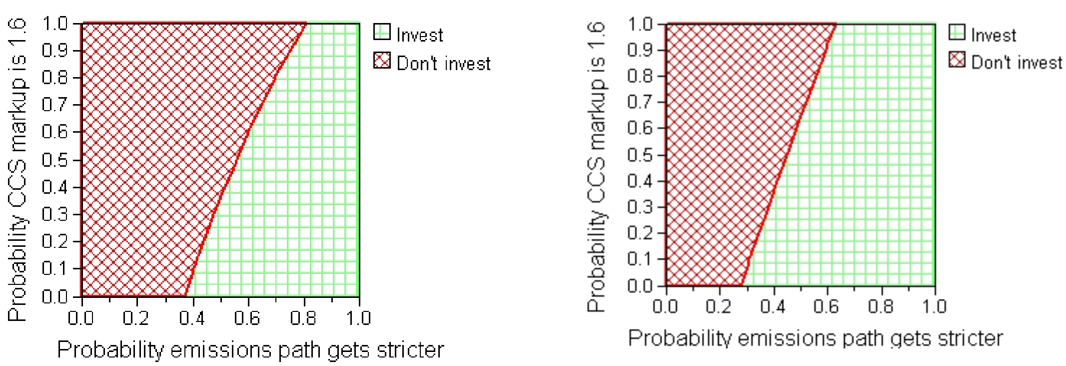

Figure 19. Probability space diagram: Uncertainty of gas resource size held constant

Figure 19 shows the results of a two-way sensitivity test varying the probability of the emissions path getting stricter or less stringent, and the probability of the CCS markup being high or low, while the probability of the large gas resource is held constant at 0.1 and 0.9, respectively. The horizontal axis goes from the less stringent policy at 0 to the stricter policy at 1, and the vertical axis runs from a CCS markup of 1.4 at 0, to a markup of 1.6 at 1. All the intermediate points on

[10] The same pairs of 2-way sensitivities could have been carried out for extremes of 0 and 1. However the range 0.1 to 0.9 is sufficient in demonstrating the emerging trends in the results.

the graph represent an individual set of probabilities, and the optimal decision is calculated as per the explanation in section 8.3 in the appendix.

The colors of the shaded regions indicate the optimal decision. The green area shows where CCS investments are beneficial, where there is an option value to investing, and in the red areas choosing to invest is creates greater welfare loss than not investing. Both plots confirm that when the likelihood of the emissions policy becoming stricter is low, the decision not to invest is always optimal. Conversely, when the probability of the emissions path getting stricter is high, then the best decision is to invest. This can be seen from the graphs with the predominantly red, 'don't invest' region on the left, where the emissions path is less stringent, and the green 'invest' area on the right where the emissions path is stricter. This fits with the result of the one-way sensitivity in section 4.2.1.

The diagonal slope of the boundary line between the decision regions shows that as the likelihood of CCS being more expensive increases, a higher probability of stricter emissions paths is required to make CCS investments worthwhile. The intuition is that we should not subsidize a technology that will be higher cost than alternatives once capacity constraints are eliminated.

Comparing the two graphs, we see that the overall shape is similar, telling us that within the range of gas resource uncertainty explored, the gas resource uncertainty has only a limited affect on the optimal decision. The scenarios differ such that when the probability of a large gas resource is 0.9, then there is a bigger range of CCS costs and emissions pathways that benefit from investment. This is indicated by the larger green area in the graph on the right relative to that in the left.

This is somewhat counter intuitive, as one might imagine that in a world with a small gas resource where gas is expensive, CCS would be in high demand, and therefore early investment to speed-up learning would be beneficial. However this is not the case. The reason why a smaller gas resource leads to recommendations not to invest in CCS under more conditions is two-fold.

When the gas resource is large investments cause CCS to enter the market much sooner than it would have done without financial support. When the gas resource is small, CCS enters the market earlier. Although the funding does cause CCS to be built earlier, the investment makes less of a difference to the timing for when CCS begins to enter the market and reduce costs, as with a small gas resource it would have become economical sooner anyway. Therefore, since the investment makes less of a difference to CCS consumption, the benefits are less.

Secondly, the small gas resource also raises demand for Advanced Nuclear. Since both Advanced Nuclear and CCS are demanded to make up for the shortfall in gas, they compete with each other. Therefore investments in a technology that may not ultimately deliver a significant portion of the electricity may be less beneficial to society. For a detailed explanation as to why this result occurs, see section 8.4 in the appendix.

This counter-intuitive result illustrates the importance of carrying out investigations such as this in a general equilibrium model like EPPA that takes account of the complex interactions between technologies. A bottom-up model would not give this result as the real feedbacks and interactions across the economy would not be captured.

The graphs in Figure 19 can be used to aid the decision of whether to invest in CCS or not. In reality it is easier to make assumptions on the likelihood of events occurring within a probabilistic range, rather than picking one particular probability. The results show that if we believe we live in world where the probabilities are within the range encompassed by the green area, then investing is the right decision. Whereas if we believe we exist in a world with probabilities that fall in the red region, then we should not invest.

Probability of CCS MU being 1.6 is 0.1 **Probability of CCS MU being 1.6 is 0.9**

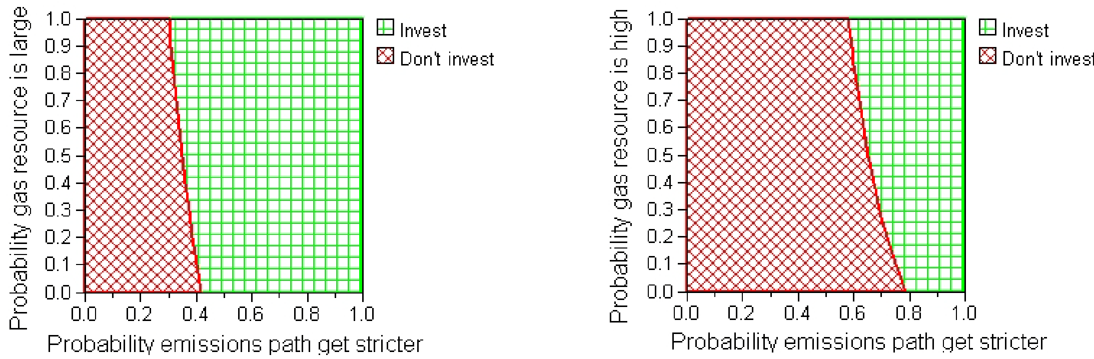

Figure 20. Probability space diagram: Uncertainty of CCS cost held constant

Figure 20 shows the optimal decisions when the likelihood of the CCS markup being 1.6 is held constant. Similarly to Figure 19, both plots confirm that when the probability of the emissions path getting stricter is low, then investment is a bad decision, but when the probability is higher it is a good decision. The slope of the line showing the transition point between decisions demonstrates that as the probability of the gas resource being large decreases, then investments should not be made. This is the same result given above, due to the interactions between gas, Advanced Nuclear and CCS, and is simply presented in a different probability space. In the graph where the probability of CCS markup being 1.6 is 0.1, there is a greater area where investment is beneficial than in the plot where the likelihood that CCS is 1.6 is 0.9. Again, this is the same result as the slope of the transition line in Figure 19 showing that when CCS is expensive, the probability that the emissions path will get stricter must be high to justify the investment.

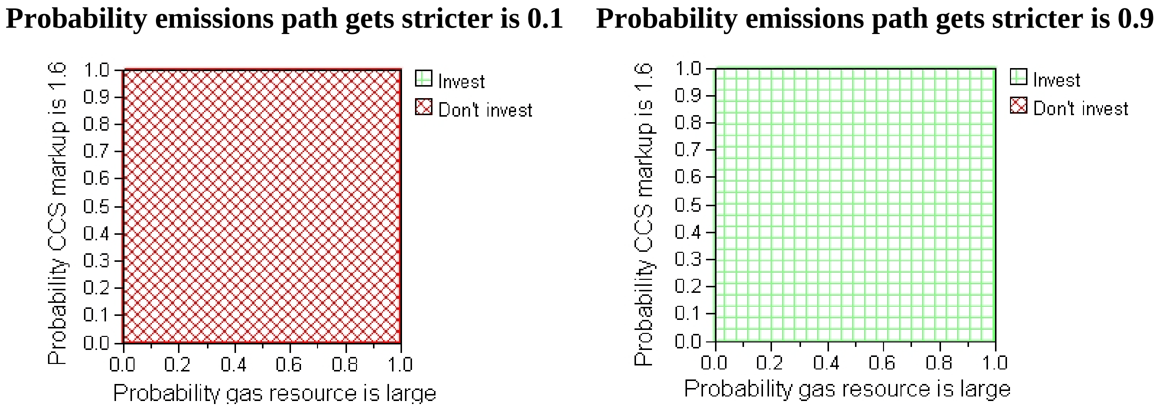

Figure 21. Probability space diagram: Uncertainty of stringency of emissions path held constant

Figure 21 shows the two-way sensitivity with the probability that the emissions path will get stricter held constant. If the likelihood of this occurring is 0.1, then regardless of how the gas resource and CCS markup vary, the decision not to invest is always optimal. Conversely, if the probability is 0.9, then the decision to invest is always best. These extremes represent the red left and green right side of the plots in all the other two-way sensitivity probability space diagrams.

By plotting both decision transition lines for each sensitivity test on one graph, it is possible to see clearly the extent to which each uncertainty affects the optimal decision.

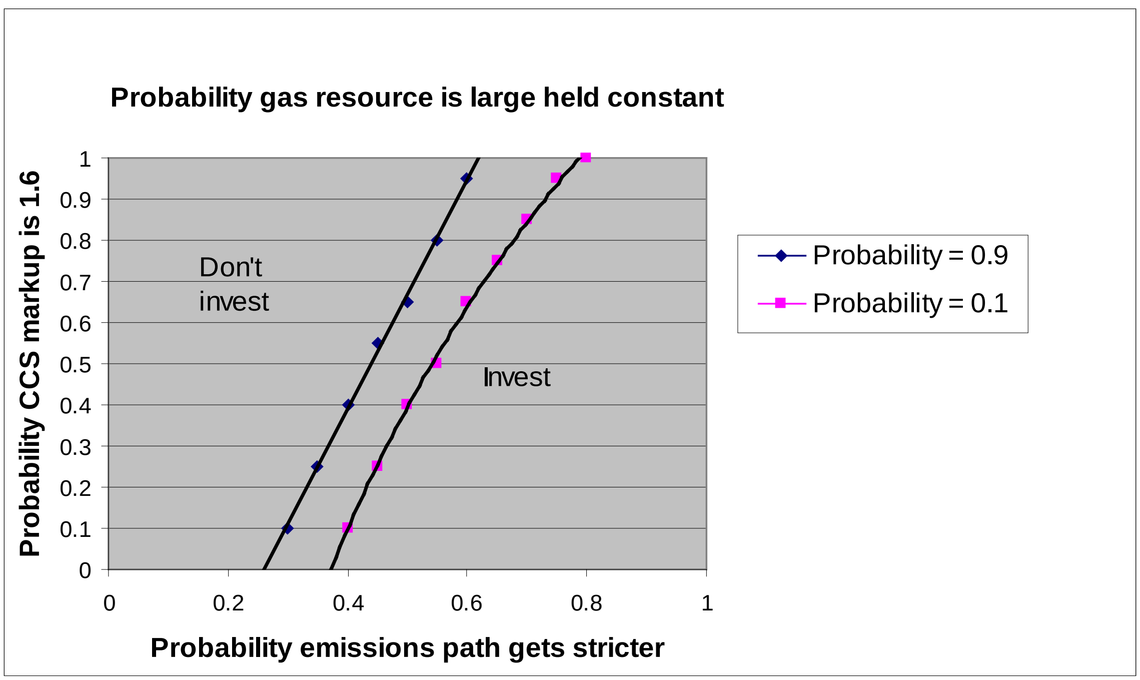

Figure 22. Decision transition lines - gas resource uncertainty held constant

In the graph where the gas resource is held constant at 0.1 and then at 0.9 (Figure 22), on the left side of the graph it is always optimal not to invest, whereas on the right side it is always better to invest, as long as the probability of the gas resource being high is within the range of 0.1 to 0.9. The optimal decision in between the lines depends on what the probability is in between this range.

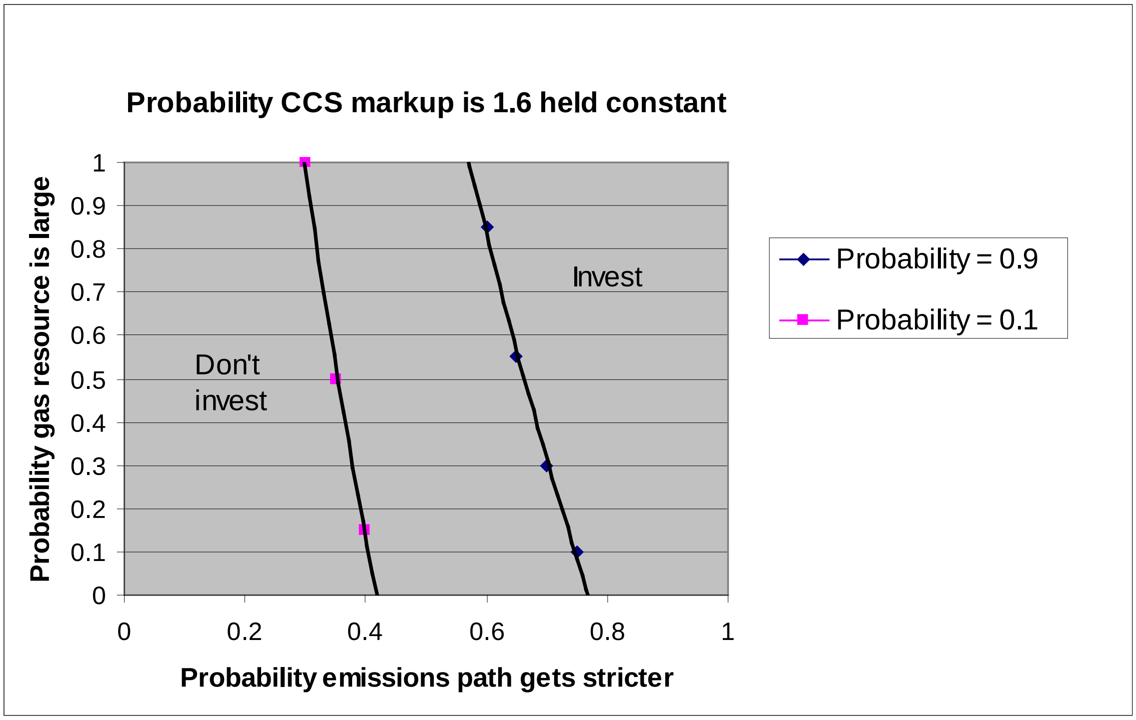

Figure 23. Decision transition line -CCS cost uncertainty held constant

In Figure 23 the area between the decision boundaries that depends on the probability of the CCS markup is greater than in the sensitivity for the extreme values of the gas resource. Therefore the decision is more sensitive to the CCS markup than the the size of the gas resource given the range of the resource explored.

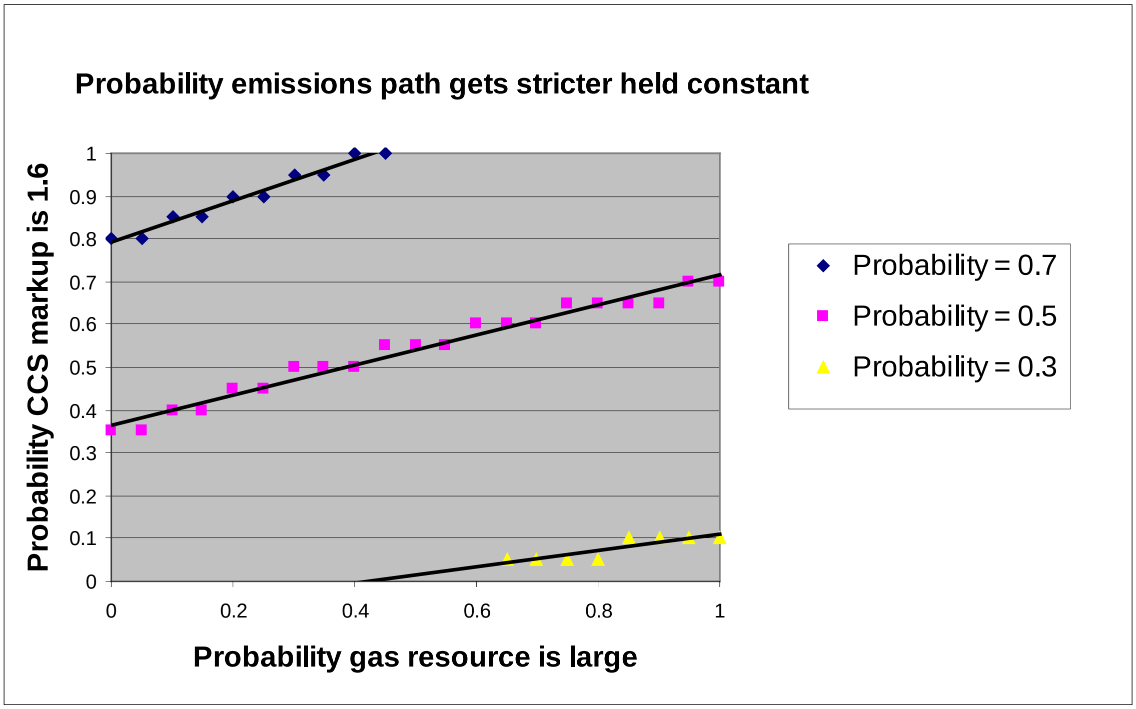

Figure 24. Decision transition line - emissions path stringency uncertainty held constant

Since at probabilities of 0.1 and 0.9 the uncertainty of the stringency of the emissions path, the optimal decision does not depend on the other uncertainties at all, less extreme ranges are plotted here, to show how the transision line changes when the probability is held constant at different values. The decision transition lines are shown for probabilities of emissions path becoming stricter at 0.3, 0.5 and 0.7. For all the lines, the area above the line gives the optimal decision as not to invest, and below it is better to invest.

By examining Figures 22, 23 and 24, it is clear that for the uncertainty ranges chosen for this analysis that the probability of the gas resource being high or low has the least impact on the decision. This can be seen because the variation in decision transition lines is the smallest for the extreme values measured. The probability of the emissions path becoming stricter is the dominating factor for the decision, since at extreme values of 0.1 and 0.9, the other variables do not affect the outcome of the decision tree analysis at all. Therefore it is the carbon price, rather than the n^{th}-of-a-kind cost or the size of the gas resource that affects the economic viability of CCS the most in the market once the investment is stopped, making the investment decision is most sensitive to emissions policy.

The results presented show qualitatively that given the ranges assumed, there are conditions under which it is beneficial to decide to invest in CCS today. If policymakers can make asumptions on the ranges for the probabilities of each of these uncertainties, then examining these results provide insight into how to consider whether CCS investments should be made or not. Further, of the three uncertainties examined, the stringency of the future emissions policy in the USA has the most impact on whether we should decide today to invest in CCS. Therefore since this is the uncertainty driving the result, it is most important to inform our beliefs of the probability range for this uncertainty with knowledge on the issues that could affect the probabilities, such as historical analysis and study of influential political elements.

5 Interpretation of analysis

This thesis presents a framework for how to consider making investments in energy technologies, investigating coal with carbon capture and storage as a case study. The analysis raises several questions that must be considered before policymakers can consider investment policies on the basis of a decision framework such as the one presented here.

5.1 What technology should we invest in?

This study has focused on the issue of whether there is an option value to investing in a technology before it is economically viable, using CCS as a case study for the reasons given in section 2.5. The results clearly showed that there are conditions where investing in CCS is economically attractive. However, it is important to recognize that there might be alternative investment options that may be even more economically attractive.

There are many other energy technologies that could play significant roles in the electricity mix in the future, such as wind, solar, biomass, and nuclear (fission and fusion) to name a few. Before discussing alternative investment options in these technologies, it is important to recognize that CCS is unique from other low carbon emitting technologies because it will always be more expensive than conventional energy source, since coal-fired power without CCS will always be cheaper than coal-fired power with CCS. If technological advances can be made such that the costs of alternative sources such as wind, solar, or nuclear, for example, can eventually be reduced below that of conventional coal-fired power, we would switch to these energy sources. There are other motivations to encourage technology switching to renewable technologies, such as sustainability or attaining zero fuel costs. However, the only incentive to switch from the conventional energy mix to coal-fired power with CCS would be to lower GHG emissions, as this is the only benefit and there are no economic gains. Therefore, it is important to bear in mind when considering investment options that there are other incentives beyond solely climate change for investment in energy technologies other than CCS, but only climate change concerns for CCS.

Despite this difference in motivations, it would be possible to repeat this analysis for each energy technology in isolation, not just CCS, and to choose to invest in the option that provides the greatest expected value to society. This in effect could result in 'picking winners' since, investing in one technology can create lock-out of another, as was shown for Advanced Nuclear in some scenarios presented here when CCS received investments.

Lock-out is not necessarily something that we should aim to avoid, if we truly believe that the process would allow us to reach our emissions targets at the lowest cost possible. However, since there are many uncertainties on how all technologies will perform in the future and information will be obtained gradually over time, we could pick investments incorrectly and risk locking-out a technology that we may need in the future.

A better strategy would be to look for an optimal portfolio of investments across energy technologies. In this way, we could give ourselves many options of using different energy technologies in the future at reduced costs, since we do not know today which we will want to use. Furthermore, in this analysis I assume that once the decision to invest is made, the investment is constant every year for 35 years. If an investment portfolio approach is taken, we would be able to resolve some of the uncertainties, such as technology costs, as we build capacity and learn. We would then be able to alter the investment portfolio over time, shifting investments from technologies that appear less viable to the technologies that we find are more cost-effective.

This strategy could be modeled using the same framework as the one presented in this thesis. The decision today would be between several investment portfolios across technologies. The model would then include a second stage decision after an uncertainty node, such as the technology costs, or any other source of uncertainty that we would wish to learn about before deciding to shift investments. The second stage decision would allow an adjustment in the investment portfolio. The decision analysis could be extended to have more than just two stages, depending on the potential timing of learning about technologies and resolving uncertainties, and the flexibility of the investment scheme.

As with the analysis in this thesis, for an investment portfolio study such as described here, it would be imperative to use a CGE model, such as EPPA, that takes account of feedback effects in the economy, since we are not investing in one technology in isolation, and the interactions between all energy technologies are critical to understand. Compared with an analysis of a single technology, a decision framework for the technology portfolio decision is likely to provide additional and greater insight for present day policy design.

5.2 How should we make investments?

This thesis has demonstrated that under some circumstances, investments in CCS are beneficial to society and provide an option value. An analysis of an investment portfolio across energy technologies would likely yield a similar result, albeit potentially under different circumstances. This then raises the question of who should make these investments. This is not a question that can be investigated using EPPA since there is only one representative agent in the model. However, it is an important issue that must be considered if investments could be beneficial to society.

The metric in this analysis by which the decision of whether to invest or not is social welfare, rather than returns on investment. Industry and private companies ordinarily make their investment decisions based on profitability rather than social welfare, and therefore would not necessarily choose to undertake an investment based on the analysis presented here. It is, however, the role of government to take actions to improve societal welfare, and therefore it is the responsibility of public policymakers to recognize whether energy technology investment should be made, and if so, how to encourage such an investment to be made. There are many reasons why private industry may not make the investments independently in early stage energy technologies. There are also many difficulties that government is faced with when encouraging these investments. This section discusses the issues involved and suggests mechanisms policymakers should consider when determining how the investments should be encouraged.

There are market failures that private industry is faced with when investing in R&D and new technologies. Spillovers can occur, such that a portion of the benefits of the investment could provide rents to others who don't make the original investment. This concern of non-excludable returns on investment is a disincentive to provide funding for new technologies, and therefore leads to undersupply of early-stage technology investment in the marketplace. This is an example of Olsonian inaction where there are concentrated costs and diffuse benefits (Olson, 1982).

Another reason why private companies would under invest in early stage expensive energy technologies is because of the uncertainty over the US emissions policy, as described in section 2.1.2. If a carbon cap were set by one administration, sparking investments in clean technologies by the private sector, only to be repealed or made less constraining by a later administration, the investment would result in considerable losses for the company. The issue of high risk and uncertainty over energy policies adds to the concern of spillover effects for the private sector, such that although we may find that society as a whole would benefit from early investments, private interests to not align with the social concern, and therefore investment will be underprovided.

Economists would argue that market failures provide the only justification for government intervention in the market. Government can act to correct these failures either through price incentives or by direct control, such as standards. However, correcting market failures is not a straightforward task, and government can easily make mistakes in the process.

A fundamental issue in attempting to eliminate market failures is that we must assume that we know how the market should behave, and therefore if we simply price everything correctly then all our problems will be solved. However, it is almost impossible to know what the 'right price' is, unless it is determined through competitive economic markets. Therefore, even though governments can act in society's best interests, government policy will never be as efficient as a price established through the market (Viscusi et al., 2005).

There are an abundance of factors that could intervene with elements throughout the policy making process that could result in a policy that does not simply correct the market failure. Examples of institutional failure that can create problems include the difficultly in balancing an efficient, one-size-fits-all policy approach versus individually tailored costly programs, within very large complex institutions such as government agencies. Another is a misalignment of personal or institutional incentives of governing officials and social interests (Allison & Zelikow, 1999).

Another problem is that although government agencies can be staffed with intelligent, knowledgeable individuals, it is still possible to make decisions about investment in technologies that turn out not to provide the returns anticipated. Further, due to the fact that administrations can change every four years, investment programs can change drastically in short periods of time. For example, by the beginning of the first decade of the 21st century, hydrogen power had begun to receive significant attention as a potentially clean and abundant fuel to replace gasoline in cars. In his 2003 State of the Union Address, President Bush proposed $1.2B in funding for the Department of Energy’s Hydrogen research program (CNN.com, 2003). However, today many energy experts believe that hydrogen is not a viable fuel for cars in the foreseeable future and will not help tackle the problems of climate change in a timely manner[11] (Romm, 2004). The Obama administration disagreed with investing such large sums of money in hydrogen research and cut the funding set by the fiscal budget by $100m in 2009 (Scientific American.com, 2009).

The Bush administration’s plan to invest heavily in hydrogen fuel cells may not have resulted in the socially optimal outcome. The Obama Administration’s halt to the program could either be considered beneficial as it stopped the unnecessarily large investment in a technology that was not going to reduce in cost in the near future, or for some is viewed as stalling the development of a much needed technology. Therefore, either government made a bad decision and invested in an unpromising technology, or if the reader agrees with hydrogen research, the short timeframe of administrative support resulted in a drawback of funding that was not committed until returns on the investment were realized. Either way, since the government must make choices in determining which technologies to support, which will be welcomed by some and opposed by others, this is less efficient and welfare optimizing than a market which would automatically determine which technologies would prosper by matching supply with demand.

[11] However there is a community that still believes in the possibility of hydrogen fuel cells and a hydrogen economy (Clark II & Rifkin, 2006).

Although there are difficulties associated with government attempts to correct market failures in early energy technology investments, interaction with the market is necessary if we believe that funding would result in benefits to society, as the investments from the private sector will not be sufficient due to spillovers and the concern over policy uncertainty.

Table 8. Policy mechanisms for inducing investment

Innovation type	Policy sub-category	Policy mechanism
Demand-pull	Carbon pricing	Cap and trade
		Emissions tax
	Mandates	Portfolio standards
		Emission Performance Standards
		Design Standards
	Subsidies	Tax Credits
		Bonus Allowances
		Feed-In-Tariffs
		Government financing
Technology-push		Direct RD&D spending
		Indirect incentives for Private RD&D
		Knowledge transfer opportunities

There are many different ways that government can induce investments in technologies. Hamilton et al., (2009) categorize the options available into demand-pull and technology-push options, shown in Table 8. Each policy mechanism has advantages and disadvantages associated with it and there is a wealth of literature discussing the attributes of each (Hamilton et al., 2009; Saidur et al., 2010; Kubert & Sinclair, 2009; Wiser et al., 2007; Bolinger et al., 2009; Doris et al., 2009). Policymakers must decide which investment tool is most appropriate for the energy technology investments that benefit society the most, and use these mechanisms to ensure the correct level of investment.

5.3 What are the 'true' probabilities?

In order for this analysis to inform investment decisions, policymakers should examine the results presented bearing in mind their own view of the likelihoods of the uncertain events that are considered. Using the decision model, we would like to be able to determine whether we fall within the probability space that recommends a particular investment decision over another, and how robust this recommendation is.

We can educate ourselves so that we can try to improve our assessments of whether we believe our circumstances place us in a particular probability space that recommends an investment choice. For example, for the stringency of the emissions policy uncertainty, we can analyze historical evidence of policies that have been updated, trends in scientific findings on climate change, and political allegiances and lobbies that could press for policy changes in the future. For uncertainties over the costs we can use cost curves from the historical developments of other large-scale technical processes, and compare ranges across different examples to give a spread of cost reductions. For the gas resource size, we can examine historical data on the accuracy of past estimates, and the evolution of techniques to provide more accurate estimates.

Further, the sensitivity analyses such as those presented in this thesis indicate the uncertainties that will drive decision changes the most. In this study, the decision is most affected by the stringency of the emissions path, and least by the gas resource. Therefore, for the case study presented here, we should consider our investment choices giving greater weight to our belief over the stringency of the emissions path uncertainty, and make substantial efforts to inform this assumed likelihood with historical facts and evidence.

However, as much as we educate ourselves, ultimately our estimates of the likelihood of the uncertainties considered are subjective to our own beliefs about the future, and there are no 'true' objective probabilities. Therefore, in making investment decisions, policymakers should use the analysis framework presented to help inform their investment decisions, and to compare the results of sensitivity analysis with their subjective beliefs about the probabilities of the uncertainties.

5.4 What are the limitations of the model?

The purpose of this study is to investigate whether option values exist for investing in CCS. When using any model to provide insights into the ways in which the future energy technology mix could evolve, we must make many assumptions. There is rarely universal agreement over these assumptions, and if we do not believe the underlying assumptions to be true, and the results are sensitive to the assumptions, then it follows logically that we should not trust the result of the model. The results presented here are consistent for one set of assumptions in the model.

One of the assumptions made in this thesis is that certain energy technologies are constrained. For example, renewables do not penetrate in the energy market because of their costs and issues of intermittency. This study does not consider any storage or backup generation that could eliminate this issue, making renewables more competitive. Morris (2009) introduces wind with biomass and wind with gas backup generation backstops into EPPA to examine the greater role renewables could play if intermittency were not an issue. The existence of these technologies could be a more realistic assumption than just wind without any backup generation. However the current estimates of the cost are much greater than any of the other energy technologies that are modeled and so they were not included in this study, since there are other cheaper low carbon alternatives available and so wind with backup generation would have no significant demand.

The purpose of investment in CCS in this study is to induce innovation so that experience can be gained, technological readiness achieved, and costs reduced to n^{th}-of-a-kind. As explained in section 2.4, innovation can be thought of as either learning-by-doing, or R&D. This study uses a model that represents capacity building in such a way that technology costs are affected in a manner similar to learning-by-doing. Therefore, the results apply only to innovation of this type, and do not take R&D innovation into account. Since modeling innovation as R&D means that costs are incurred, it is likely that taking account of R&D innovation would make the investment choice more expensive, and therefore results could differ from a model with learning-by-doing innovation in that the optimal decision would be not to invest under a greater range of circumstances. Therefore, an important extension of this study would be to carry out a similar analysis, and the extensions suggested above, using a model that does represent innovation as R&D, for example by using a forward looking model such as the one developed by Otto and Reilly (2006). Extending this study to a new model would confirm whether the results are robust across the two innovation modeling approaches, and would show how great any discrepancies are.

If the same general trends observed are similar, this would provide further validation for using an analysis framework such as the one presented here to decide whether we should make investments. Further, since it is likely that an approach with learning-by-doing would have more results where investment leads to in greater benefits to society than a model with R&D innovation, this would motivate an investigation to determine which investment inducing mechanisms lead to R&D innovation, and which give learning-by-doing innovation. This would allow us to choose the investment mechanisms that lead to greater benefits under more circumstances, which most likely would be mechanisms that induce cost reductions through learning-by-doing.

6 Conclusions

The results of a computable general equilibrium (CGE) model were used within a decision analytic framework in order to determine whether investments in coal-fired power with carbon capture and storage (CCS) under uncertainty, where capacity building takes account of learning-by-doing, are beneficial to society as a whole.

6.1 There are conditions where CCS investments create an option value

For certain ranges of probabilities for the uncertainties that would affect the demand for CCS technology, investing in CCS does provide benefits to society. Therefore there are conditions where early investments in CCS, before the technology is cost-competitive, have an option-value. This is because of the interaction of two effects – uncertainty and capacity building that leads to innovation through learning-by-doing. Technology can be built out at a much faster rate when early investments are made due to learning-by-doing and cost reductions from early experience. Since we face uncertainties, there may be circumstances in which the demand for CCS will increase more than we thought it would, and the ability to rapidly expand CCS use at n^{th}-of-a-kind costs will lower the overall cost to society of meeting the greenhouse gas (GHG) emissions policy. When the likelihood of circumstances where CCS demand will increase is high, then CCS investments should be made. These probability ranges are different for the three uncertainties explored, and the results depend on the value of all three simultaneously, but general trends for each emerged from the analysis.

Stringency of emissions path: If the likelihood of the US greenhouse gas emissions policy becoming stricter in the future is sufficiently high, then investing in CCS today is beneficial. This is because demand for CCS will increase when the emissions path becomes more constraining, and so the ability to build out the technology rapidly at low cost reduces the overall cost of meeting the emissions target. However, if it is more likely that the emissions path will become less stringent, investing in CCS is overall more costly to society compared with not investing.

Size of US gas resource: If there is a high probability that the gas resource is small, leading to higher gas prices, then investment in CCS is less beneficial than when the gas resource is large. This is a somewhat counter-intuitive result and is due to the interactions between several energy technologies. When the gas resource is small, CCS would have been economically competitive earlier without investment than under the large gas resource scenario. Further, when the gas resource is small CCS is forced to compete with Advanced Nuclear, even when investments are made. The result of these two effects is that the benefits from investment are less when the gas resource is small (for a full explanation see section 8.4 in the appendix).

Cost of CCS: If it is highly likely that CCS n^{th}-of-a-kind costs are low compared to other available technologies, then investing in CCS is beneficial, as it is probable that CCS will be demanded in the future and so being able to build it faster and more cheaply (which you can do when there is investment) reduces the cost of meeting the emissions targets. As the probability that CCS has higher costs increases, investing provides less benefit as other technologies such as Advanced Nuclear are more cost-effective.

6.2 Each uncertainty affect the investment decision to different extents

The size of the US gas resource has the least impact on the decision of whether to invest or not. The cost of CCS technology has an intermediate effect. The stringency of the emissions path has the greatest effect on the decision. The demand for CCS is affected most by the emissions policy, as this determines the carbon price. Ultimately it is the carbon price that will most affect the economic viability of CCS in a market after technology-push strategies, and therefore will have the greatest impact over whether investment in CCS today has an option value to society. Therefore policymakers should ensure that their beliefs of the likelihood of the future emissions path stringency are well informed by historical fact and should place the most weight on this factor when making investment decisions.

6.3 General equilibrium modeling is important for capturing feedback effects

Using a general equilibrium model for this analysis is important as feedback effects that impact the results are captured that otherwise would not be taken into account if a different type of model were used. For example, the result that CCS investment when the gas resource is low brings lesser benefits to society, is only captured because CGE models represent the feedback effects across the different technologies. Another example is that in some scenarios, CCS investment led to Advanced Nuclear being locked-out of the electricity market. Clearly investments have more effects than simply changing the costs of meeting an emissions target. Understanding how financial support for one technology can affect others is necessary for policymakers to appreciate since energy technologies do not operate in a vacuum. Therefore it is important to use CGE models for analyses such as this as otherwise these results caused by interaction effects that would occur in the real world would not be reported.

6.4 The discount rate affects the decision of whether to invest

When benefits from CCS investments exist, they will be realized towards the end of the century. Therefore, the choice of discount rate affects whether the investment will be beneficial or not, and to what extent. A very low discount rate creates a trend towards high benefits from investment, since the large benefits that occur later outweigh the near- term costs of the investment. Conversely a high rate discounts the benefits more heavily, eventually making the ‘benefit’ negative so that deciding to invest is worse than not investing. The negative benefit, (i.e. the cost to society of choosing to invest) with a high discount rate is limited by amount invested. If the rate is very high (on the order of 10%) the negative benefit of investment tends to zero since the dollars invested are also discounted. Therefore with a high discount rate, although the investment is a bad decision, the cost is bounded by the upfront investment. At a low discount rate, when investment is a good decision, the upper bound on the benefits is the difference in welfare in dollars summed over every year.

6.5 Framework for energy technology investments

This study examines whether investments in CCS are beneficial to society as a whole, which is important since currently investments of large amounts are being considered in Congress, and these policies should be evaluated appropriately. However, an extended purpose of this investigation is to examine a new framework for considering investments in any energy technology, and to determine whether option values exist given that we face uncertainty and learning-by-doing exists. Therefore, policymakers should not read these results as justification to invest in CCS, but rather should apply this decision framework as a method for informing policies on optimal investment portfolios across all energy technologies. Before this system of analysis can justify any investment further investigation is required, including extending the decision framework to include investment portfolios and multi-stage decision trees, analysis of investment mechanisms, consideration of uncertainty probabilities, and modeling where R&D innovation is represented. Once these elements are investigated, this framework can then provide useful insights as to whether policymakers should encourage particular investments and induce innovation in energy technologies to mitigate climate change at the lowest cost to society.

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8 Appendix

8.1 Determination of range for CCS markup uncertainty (and Advanced Nuclear markup determination)

In order to represent uncertainty on the cost competitiveness of technologies in the decision analysis without including an uncertainty node for each technology, a set of scenarios were explored to investigate whether changing just one markup would have the same effect as varying another technology markup. Early scenario testing showed that Advanced Nuclear and CCS make up the majority of the electricity supply by the end of the century, and therefore to justify only having one technology markup uncertainty in the decision tree, tests varying the markups of only CCS and Advanced Nuclear where carried out and compared. If similar technology mixes result from either varying one markup or the other, since it is only the relative cost of technologies that matters in EPPA, this would be sufficient to justify having one cost uncertainty for either Advanced Nuclear or CCS.

Nuclear markup held constant at 1.85 | CCS markup held constant at 1.54

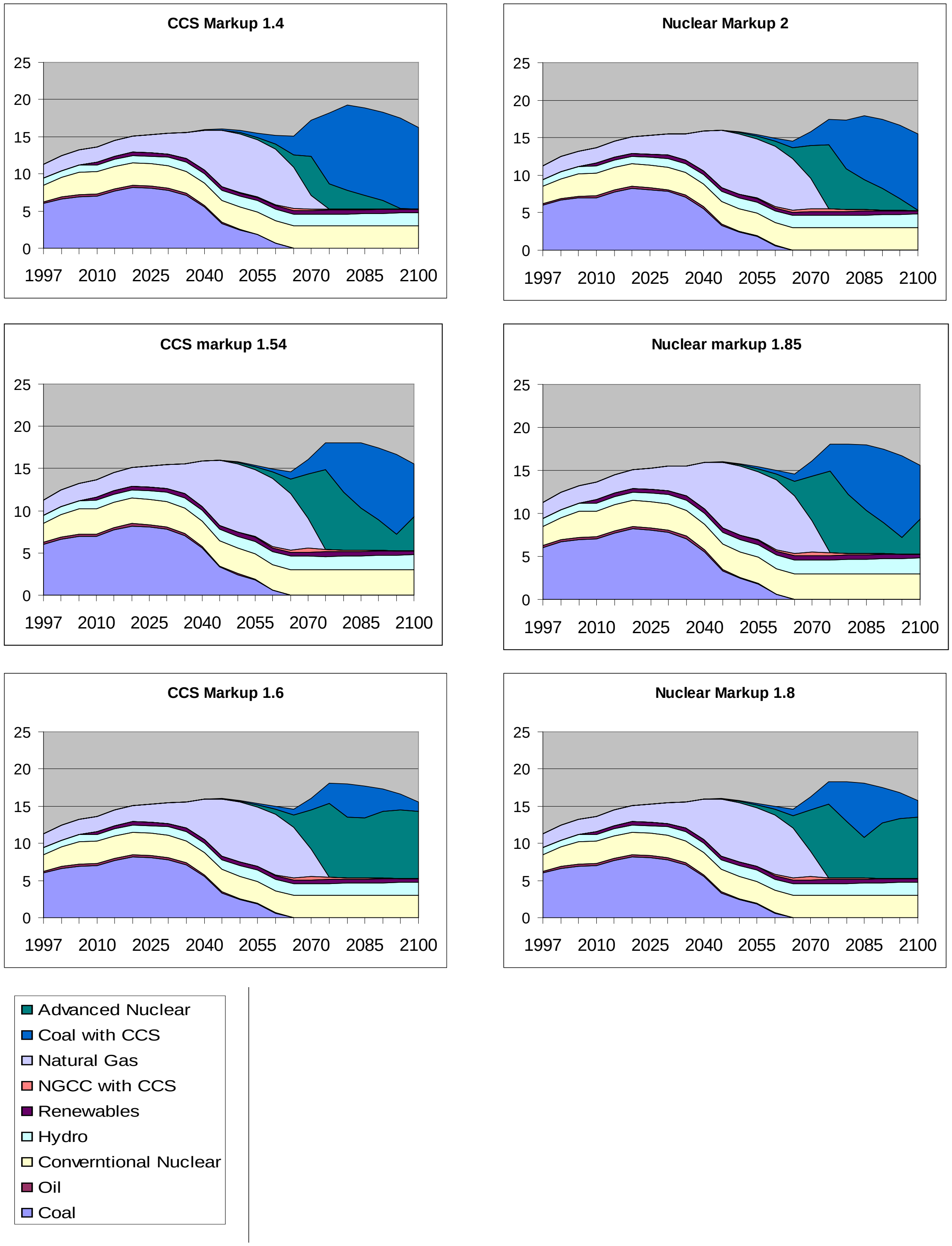


Figure 25. Technology mixes to determine range of markup for uncertainty on technology costs. Stricter emissions policy only

Figure 25 shows the technology mix for the stricter emissions policy for a variety of markups for Advanced Nuclear and CCS. In the left column, the Advanced Nuclear markup is held constant at 1.85, and in the right column the CCS markup is held constant at 1.54. Each row shows a different level of penetration for CCS and Advanced Nuclear. The top row shows a technology mix that is predominantly CCS, the second row shows an almost even mix between them, and the final row is mostly Advanced Nuclear.

The fact that the very similar technology mixes could be achieved when either markup was varied shows that simply changing the markup of one of the technologies in the decision analysis is sufficient to span a range of scenarios where CCS is both more and less competitive than Advanced Nuclear. It should be noted that the graphs in the second row are the same scenario on the left and right, as this is the base case for EPPA. Since both graphs show the same intermediate level of technology penetration from the first and third row supports the conclusion that a range of only one technology markup is necessary. Since this thesis is concerned with CCS investments, CCS cost was chosen as the technology for the markup uncertainty, but very similar results would have been found had the range of Advanced Nuclear markups presented been included instead.

The Advanced Nuclear markup of 1.85 was also determined from the above analysis. A review of the literature on the costs of nuclear power suggested that the numbers from the EIA were particularly low. If the cost numbers from the EIA are used to calculated the LCOE and mark up of the Advanced Nuclear backstop, then compared to the other potential technologies that are not constrained, it is very cheap, and it takes over the electricity market very quickly for the rest of the century. This may be the case in reality, but since we do not know if these costs are correct it would be better to examine a range of cases where Advanced Nuclear is the cheapest, and where it is not. This was the purpose of including an uncertainty on markup costs.

Since we do not wish to discount the possibility of very cheap nuclear, and yet encompass a range of options for cost competitiveness, through the above analysis several markups for Advanced Nuclear were tested, along with several ranges of CCS markups. An Advanced

Nuclear markup was determined that was close to estimates represented in the literature, that resulted in a technology mix that is predominantly Advanced Nuclear, or predominantly CCS, depending on the CCS markup range for the sensitivity analysis. Concurrently, this Advanced Nuclear markup was tested to ensure that only varying the CCS markup or the Advanced Nuclear markup about this midpoint gave the same technology mix, as shown in Figure 25.

A markup of 1.85 was found to be appropriate, since varying either the CCS markup around this Advanced Nuclear markup, or vice versa, gave the same resulting technology mix.

8.2 Base case less stringent emissions path technology mixes

Figure 26 shows the electricity mixes for the less stringent emissions policy under the base case assumptions described in section 4.1. Theses technology mixes and the NPVs of welfare in Table 7 are results from the same runs in EPPA.

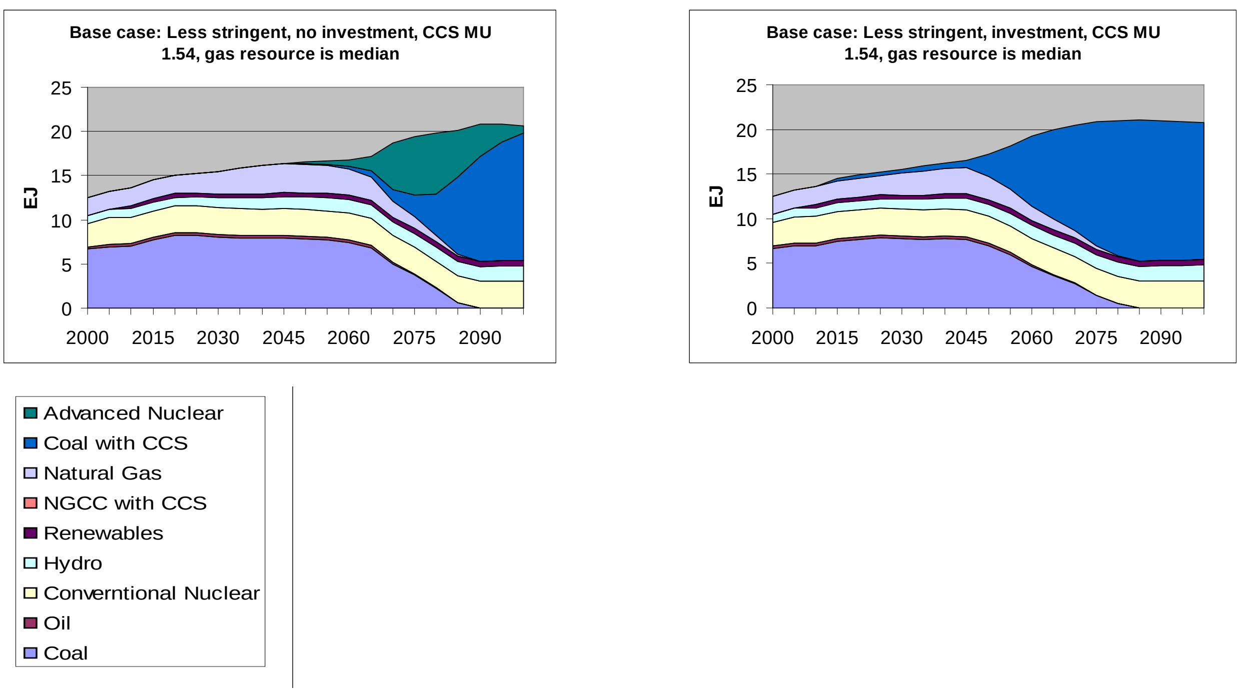


Figure 26. Technology mix for base case, less stringent emissions path

8.3 One-way sensitivity graph explained

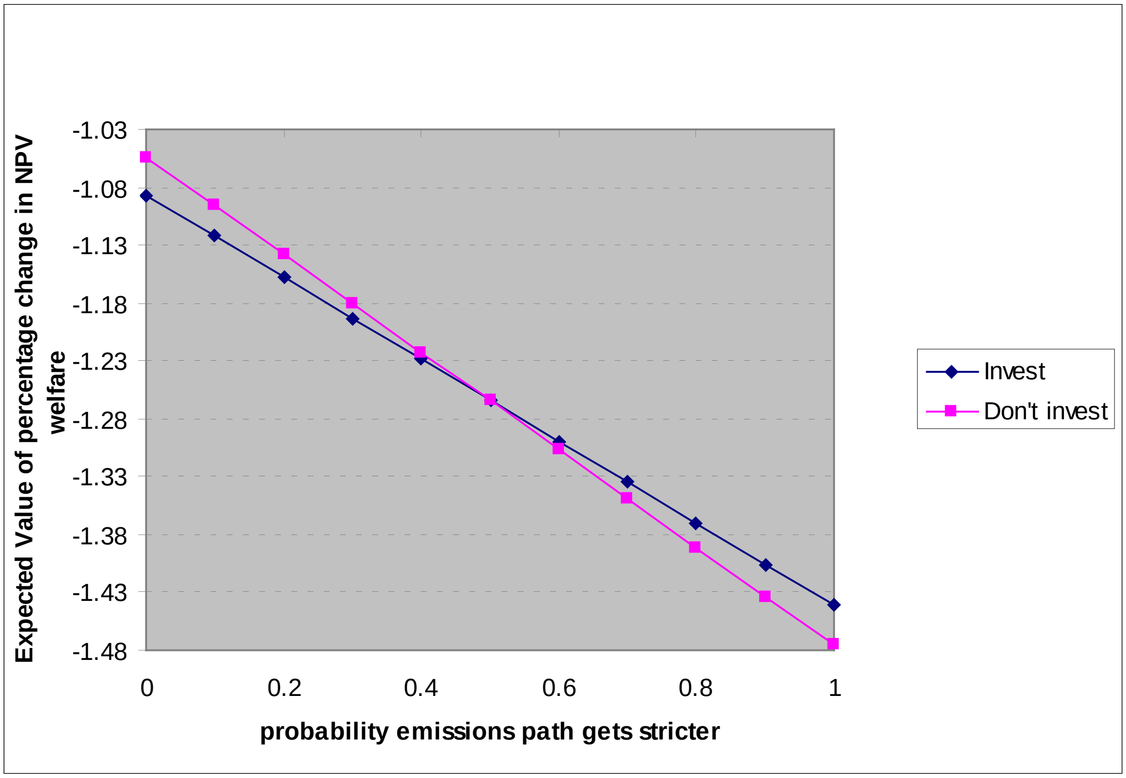


Figure 27. One-way sensitivity analysis on probability of emissions path stringency. Probability of CCS markup being 1.5 is 0.5, probability of large gas resource is 0.5

The plot shows the one-way sensitivity analysis on the uncertainty of the stringency of the emissions path. This graph is constructed using the following method:

1. The other two uncertainties (the gas resource and the CCS cost) are held constant (in this example at 0.5)
2. The probability of the emissions path getting stricter is set to 0 and the tree is solved (see below for an explanation as to how it is solved). Solving the tree gives the expected value of the NPV of welfare change from the No Policy case for both decision options. The expected values for each decision are plotted on the graph.
3. The probability of the emissions path getting stricter is then set to 0.1, and the tree solved again, to give new expected values.
4. The process is repeated, setting the emissions path stringency probability in increments of 0.1 from zero to one, and solving the decision tree every time, and plotting all the points on the graph.

The tree can be solved every time all three probabilities are defined. When the tree is solved, an expected value of the percentage change in NPV of welfare is found for each of the decision options. For example, when that the probability of the emissions path getting stricter is 0.2, which is one of the points on the graph above, the tree can be solved as explained below.

Figure 28 shows the solved decision tree where the probability of the emissions path getting stricter is 0.2.

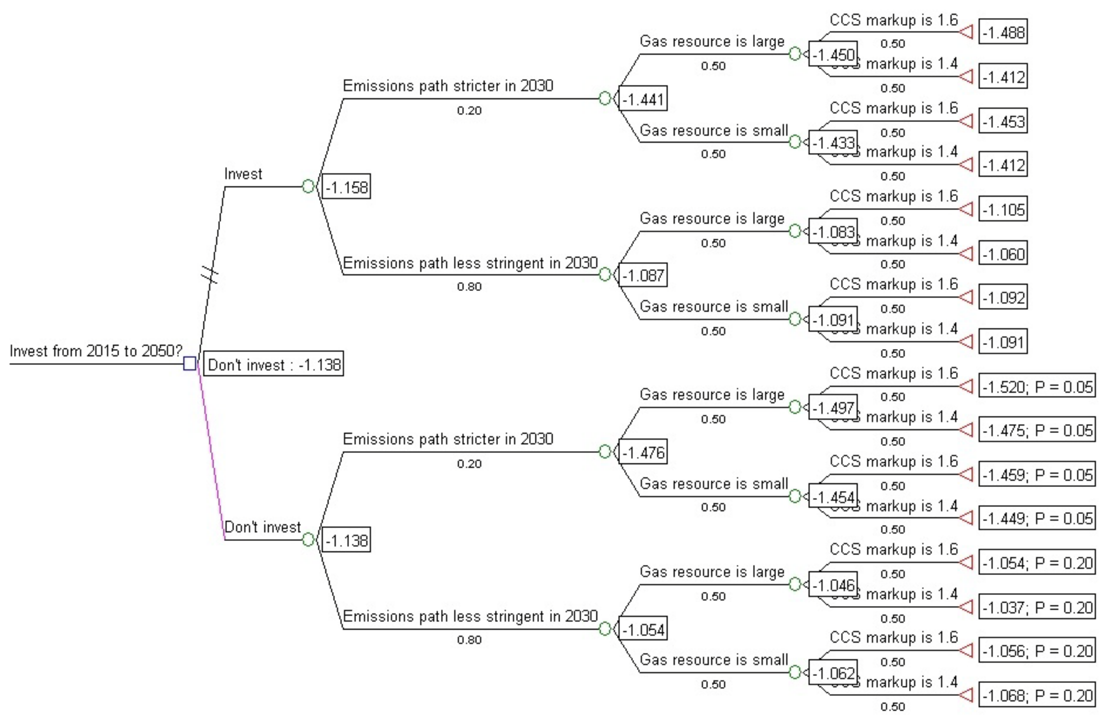


Figure 28. Solved decision tree. Probability of emissions path getting stricter is 0.2

The numbers at the end of the tree on the right are the outputs, the percentage change in NPV of welfare from the No Policy Scenario. The bottom eight outputs also include the probability of that outcome occurring. This is calculated by multiplying the probabilities along each uncertainty branch. For example, for the output at the bottom of the tree where the choice 'don't invest' is taken, the emissions path gets less stringent, the gas resource is small and the CCS markup is 1.4, the probability of that outcome is:

$$0.8 \text{ x } 0.5 \text{ x } .05 = 0.2.$$

Starting at the back of the tree with the outputs, it is possible to calculate an expected value for each node by weighing the value of each of the branches that originate at that node. This is calculated by multiplying the outcome by the probability of that branch. For example, for the top two outputs of the tree, where the decision to invest is taken, the emissions path gets stricter, the gas resource is large, and either the CCS markup is 1.6 or 1.4, the following calculation is carried out:

$$(-1.488 \times 0.5) + (-1.412 \times 0.5) = -1.450$$

-1.488 is the outcome if the CCS markup is 1.6, and 0.5 is the probability the markup is 1.6. -1.412 is the outcome if the CCS markup is 1.4, and again, 0.5 is the probability of the markup being 1.4. The figure shows the weighted outcome, -1.450, at the node of these two branches.

This type of calculation is performed at every node, 'rolling-back' towards the beginning of the tree using the previously calculated weighted outcomes. At the first uncertainty node, the values -1.158 and -1.138 have been calculated. These are the expected values of the percentage change in NPV of welfare for each decision option. The best decision is the choice that maximizes welfare, i.e. gives the smallest welfare loss. Of the two values, -1.138 is better, as it corresponds to a smaller welfare loss. As this is the better decision, only the probabilities of possible eight outcomes that could occur when this decision is taken are shown. The graph in Figure 27 plots the expected values of both decisions, and so it is clear to see which is optimal by observing their position on the plot.

The same calculation is performed for every probability of the emissions path getting stricter in 0.1 increments from zero to one, to construct the graph.

8.4 Why there are lower benefits from investing in CCS when the gas resource is small

Table 9 shows that the benefit from investing in CCS is much greater when there is a large gas resource than when there is a small gas resource.

Table 9. Benefit from investment. Stricter emissions path, CCS markup 1.6

	Small gas resource	**Large gas resource**
Benefit from investment (trillions of $)	0.231	1.192

Figure 29 shows the technology mix in the stricter emissions path case. The two graphs on the left are the results with a low gas resource, and the graphs on the right have a high gas resource. The top two graphs have no CCS investment, and the bottom graphs do.

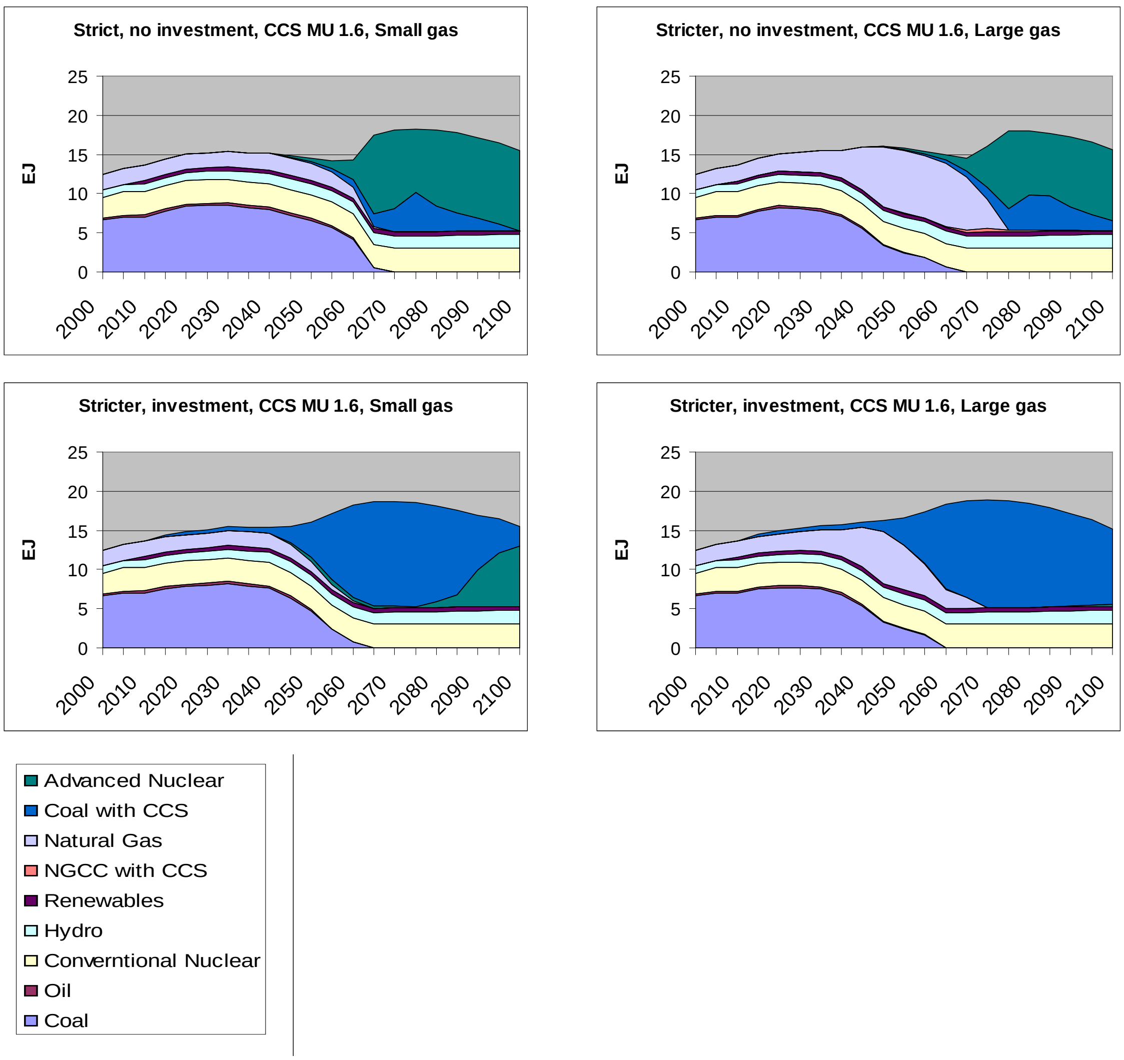


Figure 29. Electricity mix under strict emissions policy, CCS markup 1.6

When the gas resource is high or low, when there is no CCS investment, the technology mixes are very similar. There is a significant amount of Advanced Nuclear energy, since CCS is expensive here with a markup of 1.6, and it only enters the market in limited fashion as demand for energy grows, before being pushed out again by Advanced Nuclear as the cheaper energy source.

However, when there is investment in CCS, the graphs look different, depending on whether there is a large or small gas resource. With a large gas resource, CCS makes up almost all of the energy technology mix, whereas under the small gas case, CCS makes up a significant share, but is then replaced by Advanced Nuclear.

Demand for CCS and Advanced Nuclear is clearly is affected by the size of the gas resource. Therefore, in order to understand why the benefit from CCS investment under the small gas scenario is less than for the large gas scenario, an examination of the electricity provided from CCS and Advanced Nuclear is necessary.

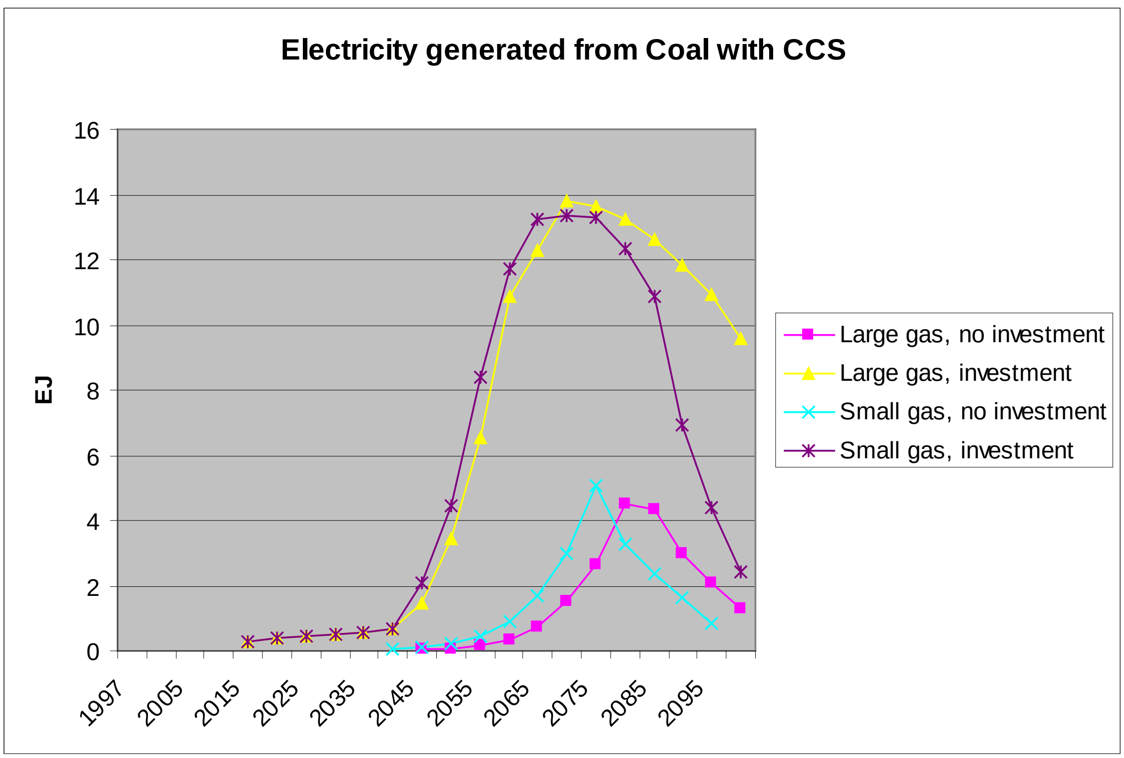


Figure 30. Electricity from Coal with CCS under the stricter emissions policy, CCS markup 1.6

Consumption of electricity from Coal with CCS is much greater, as expected, when investment in CCS is made (Figure 30). Further, when there is a small gas resource CCS enters the market sooner than with a large gas resource. This is true for the no investment case, and to a lesser extent, for the investment case.

The reason that the benefit of CCS investment under the small gas scenario is less is in part caused by this effect. Under the small gas scenario, CCS would have penetrated the market sooner without investment than the large gas scenario. In other words electricity from CCS is economically competitive sooner in the no investment, small gas case, than the large gas case. This is also true for the investment case, but here, the curves are much closer together, showing that electricity demanded from CCS when there is investment is hardly affected by the size of the gas resource. Therefore, the same dollar amount of investment results in CCS entering the market at almost the same time and rate in the large or small gas case. The key issue is that the benefit that can be gained from CCS investment depends on how much earlier the investment can bring CCS to market. Since the difference that the investment makes to the year when CCS is economically competitive is less for the small gas scenario, the benefit gained from the investment is also less.

The reason that CCS enters the market sooner under the small gas scenario is because of the carbon price.

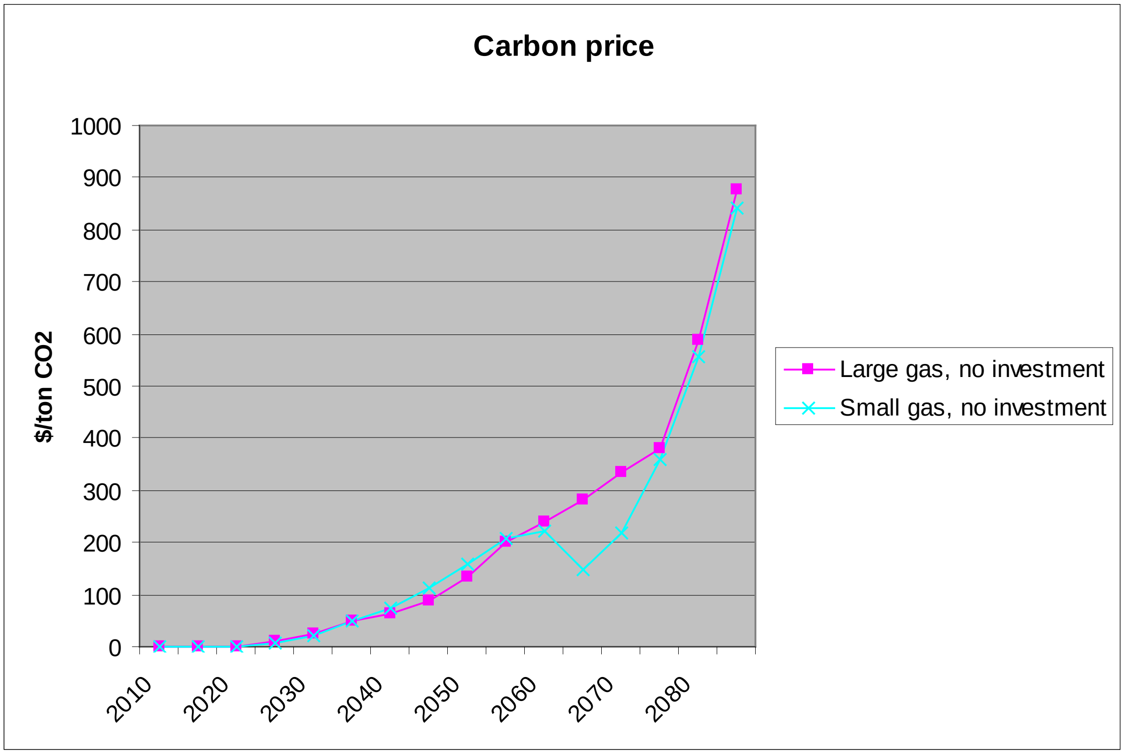


Figure 31. CO_2 permit price under stricter emissions path, CCS markup 1.6, no investment

When there is no investment, the small gas case has a higher carbon price from 2040 to 2060 than the large gas case. It is this higher carbon price that brings in CCS earlier, resulting in greater benefit of investment when there is a large gas resource.

This however creates another effect, which is to cause earlier demand for Advanced Nuclear technology, as shown in Figure 32.

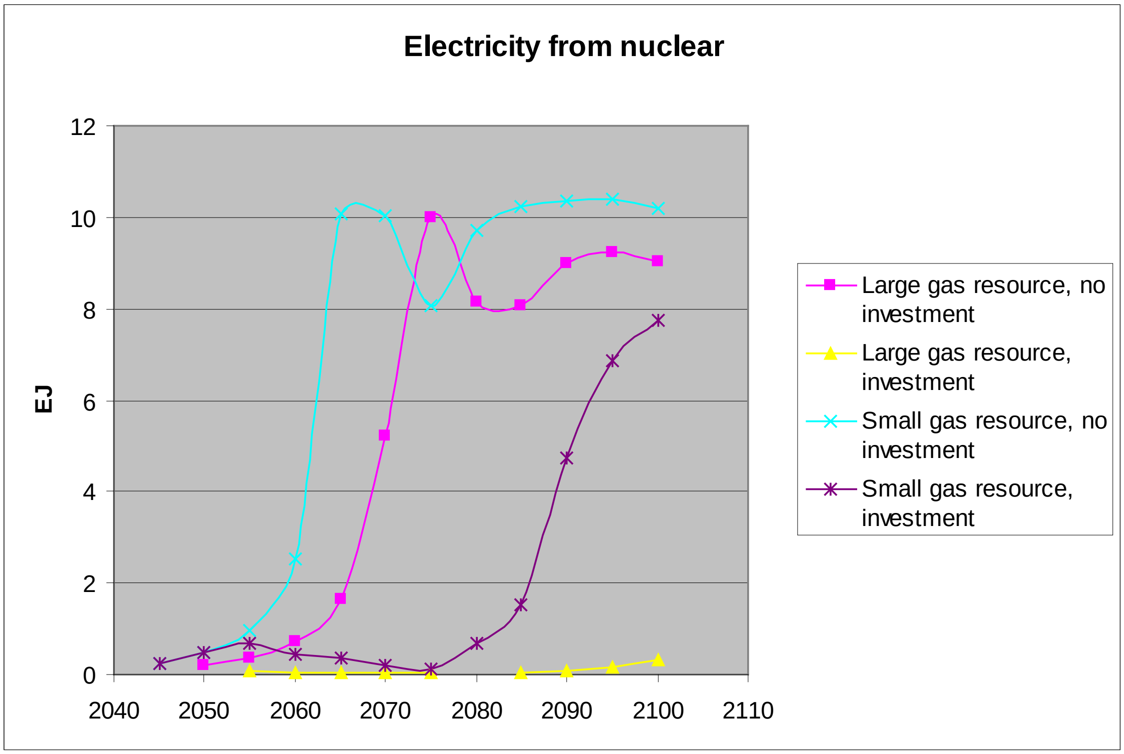


Figure 32. Electricity use from Advanced Nuclear, stricter emissions policy, CCS markup 1.6

Similarly to CCS, Advanced Nuclear is demanded earlier when there is a small gas resource. The result is that, even when investments in CCS are made, CCS will not take over the whole electricity market, and must compete with Advanced Nuclear as both technologies are demanded to compensate for the much higher cost of gas (Figure 33). This is shown in Figure 29 where Advanced Nuclear takes a large share of the electricity market towards the end of the century in the small gas scenario when investments are made. The reason that Advanced Nuclear takes such a large share of the market in the small gas scenario, but not in the large gas scenario, is that a small amount of electricity from Advanced Nuclear is demanded from approximately 2040, when it becomes economic due to the carbon price, even though CCS still makes up the vast majority of the electricity mix since it has received early investments. Because Advanced Nuclear is demanded over this period, the costs are reduced as capacity is built, and therefore eventually CCS costs rise above *n*th-of-a-kind Advanced Nuclear costs due to the expensive CO_2 emissions from CCS, and therefore Advanced Nuclear becomes cheaper than CCS. In the large gas scenario, Advanced Nuclear is locked-out, and never gets a chance to reduce to n^{th}-of-a-kind costs, and therefore CCS remains the cheapest option available and is not replaced.

It is the duel effect of CCS being demanded earlier with a small gas resource and so the investment creates fewer gains, as well as the fact that CCS must compete with Advanced Nuclear so it may not make up a large a market share as in the large gas case, that results in smaller benefits from investment in the small gas resource case.

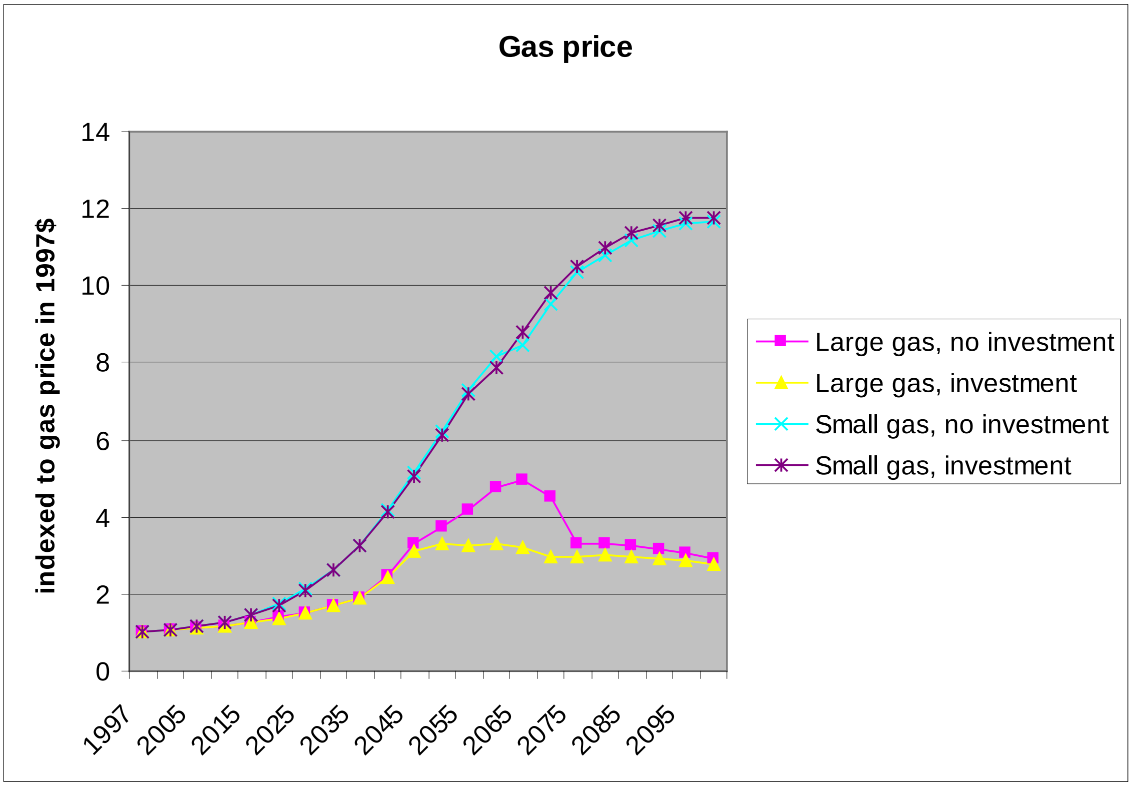


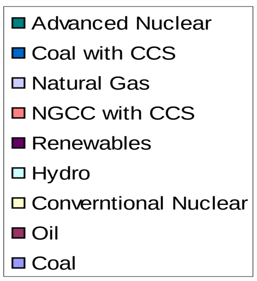
Figure 33. Gas price under stricter emissions policy, CCS markup 1.6

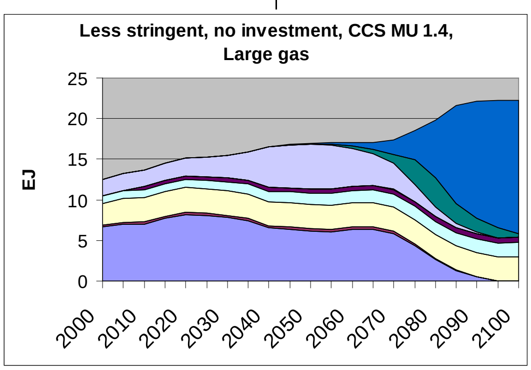
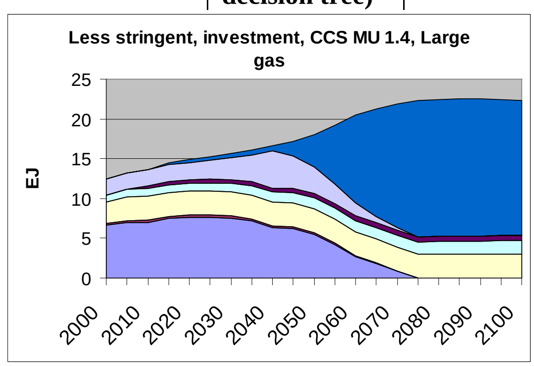
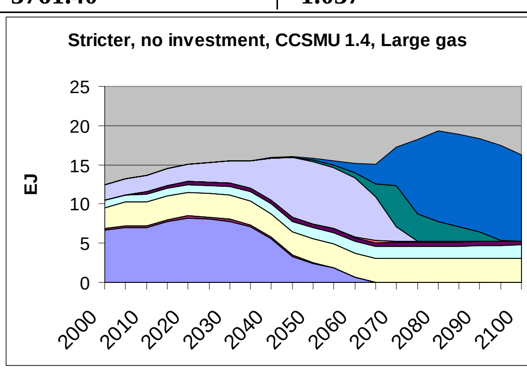
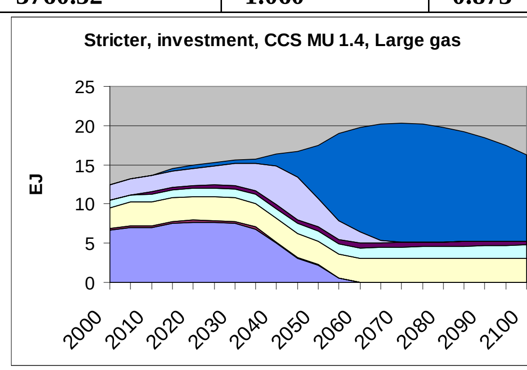
8.5 Technology mix for all scenarios in decision analysis

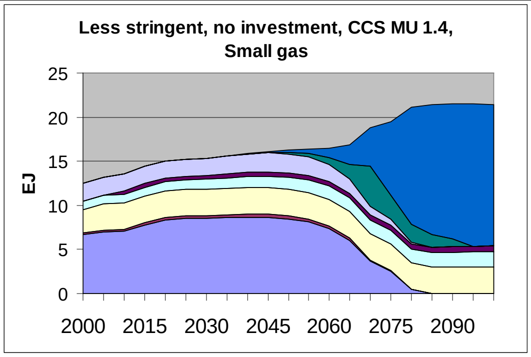
For every scenario in the tree, Table 10 shows the technology mix, the NPV of welfare discounted at 4%, the percentage differences in NPV welfare from the No Policy case (the outcome in the decision tree), and the benefit of the investment in trillions of dollars, which is the difference between the NPV welfare in the investment case and the no investment case. If the benefit from investment is negative for a scenario, then choosing not to invest is preferred to investing.

For the No policy case the welfare is slightly different depending on the gas resource. Therefore the baseline of comparison for calculating the percentage difference in NPV of welfare is different in the scenarios, depending on the gas resource. Table 11 gives the welfare for the No Policy scenario for each assumption of the gas resource, giving the baselines for the calculations in Table 10.

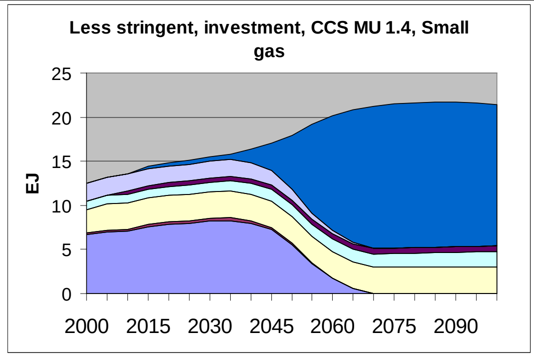
Table 10. Technology mix and welfare for all scenarios in decision analysis



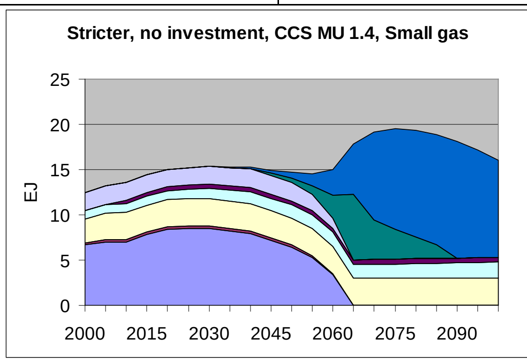
<table>
<tr><th colspan="2">No CCS investment</th><th colspan="3">CCS investment</th></tr>
<tr><th>NPV welfare discounted at 4% (trillions of $)</th><th>% difference in NPV welfare from no policy (output in decision tree)</th><th>NPV welfare (discounted at 4%)</th><th>% difference in NPV welfare from no policy (output in decision tree)</th><th>Benefit of invesmtent (trillions of $)</th></tr>
<tr><td colspan="2"></td><td colspan="3"></td></tr>
<tr><td>3761.40</td><td>-1.037</td><td>3760.52</td><td>-1.060</td><td>-0.873</td></tr>
<tr><td colspan="2"></td><td colspan="3"></td></tr>
<tr><td>3744.749</td><td>-1.475</td><td>3747.156</td><td>-1.412</td><td>2.407</td></tr>
</table>



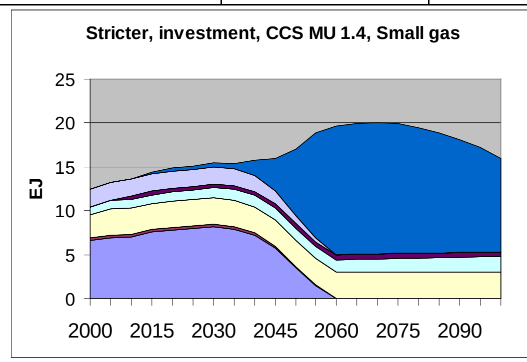
3749.499	**-1.068**



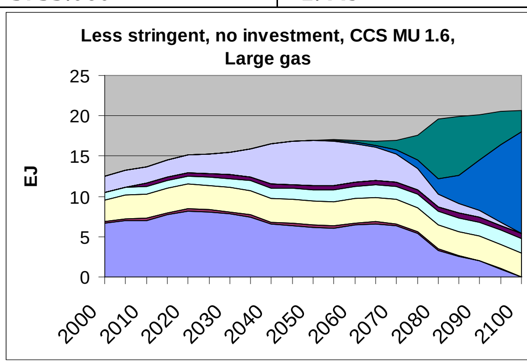
3748.617	**-1.091**	**-0.882**



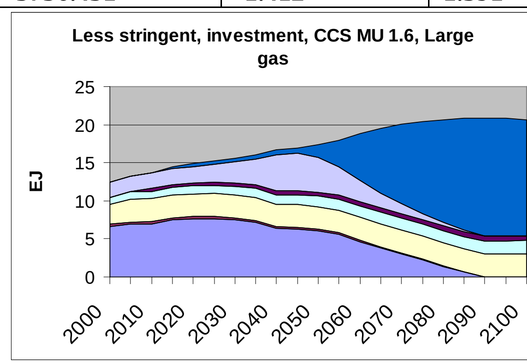
3735.060	**-1.449**



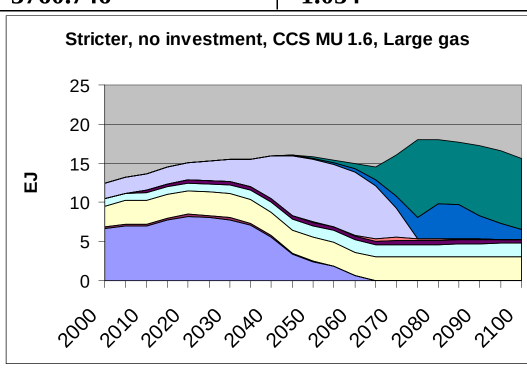
3736.451	**-1.412**	**1.391**



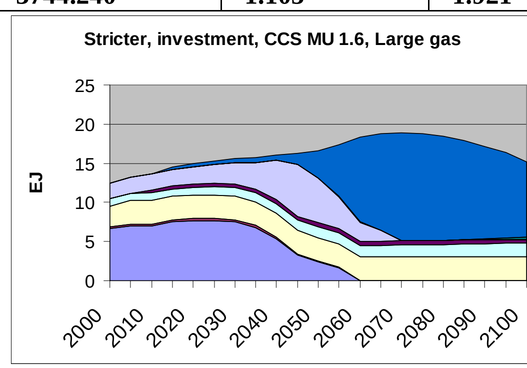
3760.746	**-1.054**



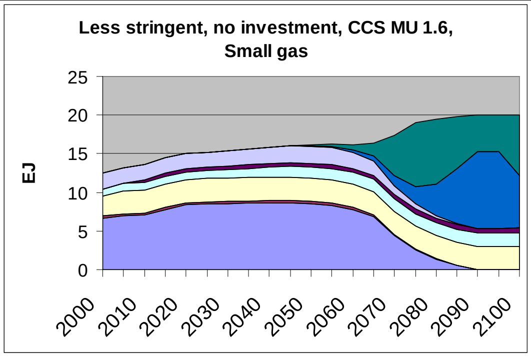
3744.240	**-1.105**	**-1.921**



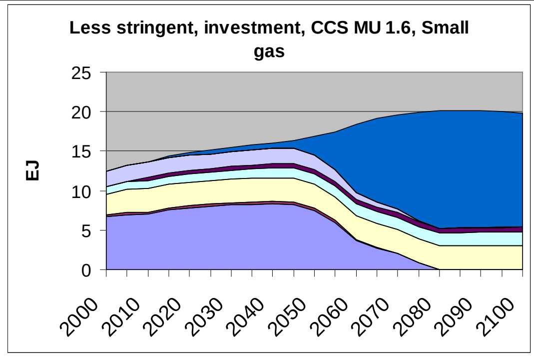
3743.049	**-1.520**



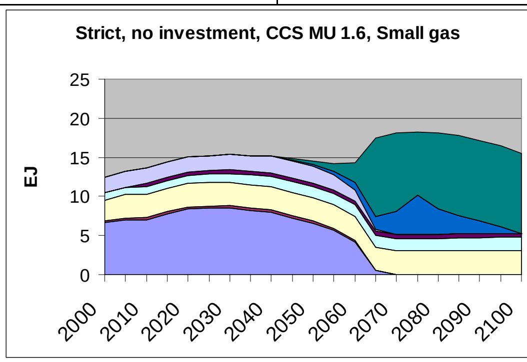
3744.240	**-1.488**	**1.192**



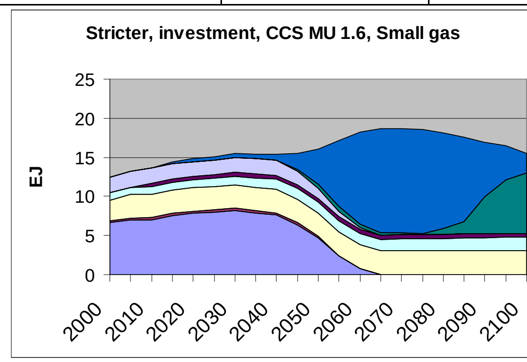
3749.941 | -1.056



3748.576 | -1.092 | -1.366



3734..660 | -1.459



3734.891 | -1.453 | 0.231

Table 11. Welfare for No Policy scenario

Gas scenario	**Small gas resource**	**Median gas resource**	**Large gas resource**
EJ	1100	1650	2200
Welfare (trillions of $)	3789.975	3797.028	3800.813