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Adoption of Renewable Energy Technologies under Uncertainty

By

Kiran Nari Torani

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

GRADUATE DIVISION

of the

UNIVERSITY OF CALIFORNIA, BERKELEY

Committee in charge:

Professor Gordon Rausser, Chair Professor David Zilberman Professor Duncan Callaway

Fall 2014

Adoption of Renewable Energy Technologies under Uncertainty

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Kiran Nari Torani

Abstract

Adoption of Renewable Energy Technologies under Uncertainty

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Kiran Nari Torani

Doctor of Philosophy in Agricultural and Resource Economics

University of California, Berkeley

Professor Gordon Rausser, Chair

This dissertation presents both a theoretical and empirical examination of the optimal allocation of public R&D investments in combination with downstream policy instruments across emerging renewable technologies. The central issue remains how best to enable technological change, and accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system.

The first essay presents a stochastic dynamic real options model of the adoption of solar PV in the residential and commercial sector, evaluating the threshold and timing of the consumer's optimal investment decision given two sources of uncertainty. Analytic results regarding the threshold of adoption under alternative regimes of R&D funding and technological change, electricity prices, subsidies and carbon taxes are derived. And we simulate the model to obtain a cumulative likelihood and timing of substitution amongst energy resources and towards solar PV under plausible rates of technological change, electricity prices, subsidies and carbon taxes.

The results indicate that there will be a displacement of incumbent technologies and a widespread shift towards solar PV in the residential and commercial sector in under 30 years, under plausible parameter assumptions - and that crucially, this can occur independent of consumer subsidies and carbon pricing policies (at \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2). In general, results across all scenarios consistently indicate that average historic consumer subsidies and carbon pricing policies up to \$150/ton CO2 have a modest effect in accelerating adoption, and may not be an effective part of climate policy in this regard. Instead, we find that R&D support and further technological change is the crucial determinant and main driver of widespread adoption of solar PV - suggesting that subsidies and taxes don't make a substantial difference in a technology

that's not viable, while research does. This further suggests that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant of widespread transition to solar and plausibly other backstop technologies – and that it should play a key role in policy measures intended to combat climate change. The results do not imply that carbon pricing shouldn't play a role in climate policy in general. Carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies – however it has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2.

The second essay examines the role of technology features in policy design, and provides a broader discussion and context to the results from the first essay. It examines the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards renewable energy technologies. And it examines the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in deployment polices, and in CO2 taxes.

We examine the notion that that optimal policies will change over time, driven primarily by the characteristics of the technology, and its stage in the innovation cycle – and that *this* will crucially determine the impact, gains and tradeoffs between alternate policy measures such as R&D policies, deployment policies, and carbon pricing policies. We find that technology and policies must be deployed in a coordinated manner such that emission reduction benefits are achieved at an acceptable cost. And we find that targeted policy should consider every stage of the technology innovation cycle - from R&D to commercialization in overcoming barriers to the development and widespread adoption of nascent technologies.

Based on our analysis and results we find that there is a pressing need for the reallocation of public resources from consumer subsidies towards public R&D budgets in emerging energy technologies such as solar PV, and plausibly other backstop technologies. We argue for an expanded role of aggressive R&D policies and increased public R&D funding – and contend that there is an imbalance in resources allocated towards adoption and commercialization subsidies relative to R&D investments for a technology such as solar PV. We contend that increased and aggressive R&D investments will be the key policy initiative in enabling the transition towards clean energy technologies such as solar PV in a sustainable manner.

When deployment policies are justified, the appropriate timing and sequencing in the technology development stage is crucial. Investments in commercialization and deployment subsidies before sufficient R&D investments and breakthroughs have occurred will be ineffective and unsustainable, or alternatively will need to be very high to have any significant impact (Torani, Rausser, and Zilberman, 2014). Widespread adoption and commercialization of emerging and unproven technologies and systems will be unlikely to occur unless sufficient major technological discoveries and improvements have taken place - which will need to be driven by appropriate and sufficient R&D

investments. The logical sequence of policies necessitates first making sufficient investments and allocating resources towards R&D and the necessary technological discoveries, which can then be followed by downstream investments to enhance adoption, experience and LBD. In general, we find that the appropriate emphasis and sequencing of R&D and learning investments is a pertinent issue, and optimal timing and allocation between the two depends in part on the characteristics of the technology itself.

In addition, while almost all economic studies find a case for imposing immediate restraints on GHG emissions, e.g. with initially low carbon taxes, we find that reasonable and plausible levels of CO2 taxes may not be effective in encouraging technology adoption and reducing emissions while clean technologies are not commercially viable as yet. To be effective in encouraging technology adoption at an early stage of technological innovation, we contend that a large CO2 tax may be needed, far larger than suggested at reasonable levels - with significant implications on distributional effects and political We emphasize that technology and policies must be deployed in a feasibility. coordinated manner such that the emission reduction benefits are achieved at an acceptable cost (Williams et al., 2012). Our results suggest that the first and most important stage does not lie in imposing CO2 taxes, but rather in investing in R&D and technological advancements. Once clean technologies are sufficiently ready, reasonably priced carbon taxes will bite to a larger extent and be more effective at plausible levels. We find that one plausible strategy would be either to introduce high CO2 taxes or to subsidize R&D first, followed by deployment and LBD policies, and then to impose reasonable carbon taxes – in which case scientific advances and technological changes would make CO2 emissions abatement less costly, and CO2 pricing would be effective at reasonable levels.

The third essay provides a precursor and basis for the other two chapters. The paper outlines an analytical framework to determine the optimal combination of renewable energy public R&D investment in combination with downstream policy instruments across the emerging technologies as an ex-ante portfolio analysis of public and private R&D under risk and uncertainty. Our framework is based on the estimation of probability distributions for potential future cost reductions resulting from R&D investments from the public and private sectors.

To date, the government lacks coordinated support of renewable energy technologies across upstream R&D investments and downstream policy instruments. Without an objective, ex-ante guide for renewable energy investment, governments are likely to promote technologies based on the effectiveness of political economic efforts. The government's policies should however depend on the technology's probability distribution of cost breakthroughs for each technology and on the environmental impact. In this paper we outline an analytical framework to develop a portfolio analysis of R&D investments in renewable energy technologies, with the subsequent analysis designed to allocate R&D investments across renewable energy technologies in a manner that minimizes the risk for a specified level of expected returns, taking into account both the expected reductions in cost and the variance of the expectations of cost reductions, and thus providing an objective benchmark for efficient allocation of resources across renewable energy technologies. Special emphasis is placed on the estimation of

probability distributions based on elicitation from experts in each field of technology in terms of the mean and standard deviation – on which we base the characterization of the underlying probability distributions on cost and productivity measures, and which forms the basis for executing a portfolio analysis of renewable energy technologies.

To my family

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Chapter 1

Introduction

The transition towards clean technologies will play a key role in our efforts to meet deeper, long term green house gas (GHG) reductions¹, beyond energy efficiency (EE) and carbon capture and storage (CCS). Meeting these goals will require a "significant reorientation of national energy trajectories" (Sagar et al., 2006) and the development and deployment of renewable technologies that are not yet commercialized. (Williams et al., 2012; Chakravorty et al., 1997; Margolis and Kammen, 1999; Goulder and Parry, 2008).

Technology and technology policies will play an important role in enabling the transition towards renewable energy technologies. The central issue in this regard remains how best to enable technological change, and accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system.

This dissertation presents both a theoretical and empirical examination of the optimal allocation of public R&D investments in renewable energy technologies in combination with downstream policy instruments across the emerging technologies.

Innovation Subsidies versus Consumer Subsidies: A Real Options Analysis of Solar Energy

The first essay, Chapter 2, considers the question of how to transition to a meaningful percentage of solar energy in a sustainable manner and which policies are most effective in accelerating adoption. We develop a theoretic stochastic dynamic real options model of the adoption of solar PV in the residential and commercial sector, evaluating the threshold and timing of the consumer's optimal investment decision given two sources of uncertainty – i.e. uncertainty in the price of electricity and the cost of solar.

We derive analytic results regarding the threshold of adoption under alternative regimes of R&D funding and technological change, electricity prices, subsidies and carbon taxes. And we develop an algorithm and simulation technique based on a bivariate kernel density estimation to derive projections of the cumulative likelihood and timing of substitution amongst energy resources and towards solar. In this paper, we apply the methodology to solar PV as an illustration of the technique given multiple sources of uncertainty, and provide a general framework to evaluate investments in competing

¹ Several US states have recently announced the goal of reducing greenhouse gas emissions by 80 percent below their 1990 levels by 2050. The magnitude of carbon cuts required is large – beyond what EE and CCS measures can achieve (Williams et al., 2012).

alternative renewable energy technologies. We simulate the model to obtain a cumulative likelihood and timing of substitution amongst energy resources and towards solar PV under plausible rates of technological change, electricity prices, subsidies and carbon taxes.

Real options analysis (ROA) is a stochastic dynamic framework analyzing investment decisions in the presence of uncertainty of the economic environment, irreversibility, and the ability to postpone the investment decision (Dixit and Pindyck, 1994). It can be interpreted as a "dynamic net present value (NPV)" which differs from traditional static "now or never" NPV breakeven models of investment, with a key result of the real options framework being that the investor will require a significant excess return above the expected present value before making the investment in light of these three factors.

In this dissertation we extend the current literature both methodologically and empirically. Methodologically, we incorporate two sources of uncertainty as an extension of the traditional single variable model and provide new analytic insights and comparative static results which elucidate the differing paradigms of ROA and NPV. Empirically, to our knowledge, this is the first real options paper to examine the question of solar energy. Further, we develop an algorithm and simulation technique based on a bivariate kernel density estimation, which is essential due to the extension of ROA to incorporate two stochastic processes, and which has general applicability and can be used to evaluate investments in alternative renewable energy technologies.

The Transition to Renewable Energy Technologies: Optimal Policies Over Time

Chapter 3 follows directly from the results of the first essay. It examines the role of technology features in policy design, and provides a broader discussion and context to the results from chapter 2. In this paper, we illustrate the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards renewable energy technologies. We examine the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in LBD and deployment polices, and in CO2 taxes. We examine the notion that that optimal policies will change over time, driven primarily by the characteristics of the technology, and its stage in the innovation cycle – and that *this* will crucially determine the impact, gains and tradeoffs between alternate policy measures such as R&D policies, deployment policies, and carbon pricing policies.

We consider the characteristics and stage of technology innovation, and the optimal timing and sequencing of policies in this regard - which we find will affect the impact of differing policy instruments, and which is noticeably absent from most studies evaluating and comparing policy instruments in environmental policy. We examine the notion that technology and policies must be deployed in a coordinated manner such that emission reduction benefits are achieved at an acceptable cost. And we find that targeted policy should consider every stage of the technology innovation cycle - from R&D to

commercialization in overcoming barriers to the development and widespread adoption of nascent technologies.

We place particular emphasis on the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in deployment policies and LBD, and in CO2 taxes. This paper examines the notion that that optimal policies will change over time, and that the technology under consideration will largely determine how and when to allocate available funds. This implies that optimal design may require differing polices for differing technologies, based on the characteristics of the technology and its stage of development. Balancing R&D and deployment investments is a pertinent issue, with a concrete tradeoff between allocating funds in one direction of the other. We contend that optimal allocation of public resources may require a different split between R&D and deployment for different technologies, based on the characteristics of the technology, its stage of development, and the gains achievable through R&D and deployment efforts. The appropriate emphasis and sequencing of R&D and deployment investments is a pertinent issue, and we explore the optimal timing and allocation between the two, which depends in part on the characteristics of the technology – which will in part determine the impact and effectiveness of differing policy incentives.

It is in this context that we also examine the effectiveness of an emissions control policy such as a carbon tax in encouraging technology adoption at the early stages of an emerging renewable energy technology, while the technology is not commercially viable. While almost all economic studies find a case for imposing immediate restraints on GHG emissions, with many researchers advocating for an immediate, and at least initially low carbon tax (even if the true SCC is unknown), we evaluate the notion that reasonable and plausible levels of CO2 taxes may not be effective in encouraging technology adoption and reducing emissions while clean technologies are not commercially viable as yet.

Managing R&D Risk in Renewable Energy: Biofuels vs. Alternate Technologies

Chapter 4 presents the precursor and basis for the other two chapters. It is an examination of the government's use of upstream R&D investments and downstream incentives across renewable energy technologies, intended to achieve commercial breakthroughs in biofuels, batteries, fuel cells, hydrogen, solar and wind energy. Each of these policy instruments is designed to alter the incentives for the use of renewable energy by making it more competitive with exhaustible sources of energy.

This paper outlines an analytical framework to determine the optimal allocation of renewable energy public R&D investment in combination with downstream policy instruments across the emerging technologies as an ex-ante portfolio analysis of public and private R&D under risk and uncertainty. Currently there is no clear, *ex ante* plan to guide upstream or downstream public support of renewable energy technologies. It is with this motivation that this paper outlines a framework to determine the optimal combination of upstream R&D investments and downstream instruments. Our

framework is based on the estimation of probability distributions for potential future cost reductions resulting from R&D investments from the public and private sectors.

To date, the government lacks coordinated support of renewable energy technologies across upstream R&D investments and downstream policy instruments. Without an objective, ex-ante guide for renewable energy investment, governments are likely to promote technologies based on the effectiveness of political economic efforts. The government's policies should however depend on the technology's probability distribution of cost breakthroughs for each technology and on the environmental impact. In this paper we outline an analytical framework to develop a portfolio analysis of R&D investments in renewable energy technologies under risk and uncertainty.

The subsequent portfolio analysis is designed to allocate R&D investments across renewable energy technologies in a manner that minimizes the risk for a specified level of expected returns, taking into account both the expected reductions in cost and the variance of the expectations of cost reductions, and thus providing an objective benchmark for efficient allocation of resources across renewable energy technologies. Special emphasis is placed on the estimation of probability distributions based on elicitation from experts in each field of technology in terms of the mean and standard deviation – on which we base the characterization of the underlying probability distributions on cost and productivity measures, and which forms the basis for executing a portfolio analysis of renewable energy technologies.

Chapter 2

Innovation Subsidies versus Consumer Subsidies: A Real Options Analysis of Solar Energy*

2.1 Introduction

The installed capacity of solar PV systems has increased dramatically over the past five years, increasing by 53% per year in the US and by 60% per year globally. While this rapid growth has partly been driven by declining costs in solar, it has primarily been driven by state and federal incentives and policy support.

Current adoption of solar PV systems without incentives remains unlikely. Notwithstanding recent declines, the high cost of solar PV renders it unable to compete with incumbent electricity technologies, even when incorporating benefits of the technology which might not have been previously accounted for (Goodrich et al., 2012; Borenstein, 2008).

Incentives to the residential and commercial sectors (which historically account for approximately 70% of installed capacity in the US) have ranged from up-front cash rebates to renewable portfolio standards, and federal and state tax benefits. Incentives have covered an estimated 3% to 50% of total system cost, and have amounted up to \$22,000 per installation (Peterson, 2011).

Yet in 2012 solar energy amounted to little over 1% of generated electricity in the US (EIA, March 2013), and contributed the smallest share amongst all renewable-generated electricity.³

^{*} Co-authored with Gordon Rausser and David Zilberman. The authors gratefully acknowledge financial support from the Energy Biosciences Institute at the University of California, Berkeley.

³ Which is ironic, since solar is by far the most abundant of all the renewable resources.

If our aim is to speed the commercialization and deployment of affordable, clean energy technologies and transition to market driven industries, then the central question remains - how do we get to a meaningful percentage of solar PV generation in a sustainable way?

Will there be a widespread shift towards solar PV, and which policies are effective and which aren't? The question is pertinent, and Chakravorty et al. (1997) suggest that the transition to backstop technologies may be the only viable solution to global warming. In this paper, we examine the prospects for future adoption of solar PV in the residential and commercial sector, recognizing that what drives the process on a sustainable basis is the consumer's adoption decision. We examine which policies will have an impact in accelerating adoption and what role solar energy will ultimately play in our future energy mix.

We use a stochastic dynamic framework, and develop a theoretic real options model to evaluate the threshold and timing of the consumer's optimal investment decision, given two sources of uncertainty – uncertainty in both the price of electricity and the cost of solar. We derive analytic results regarding the threshold of adoption under alternative regimes of R&D funding and technological change, subsidies and carbon taxes. And we develop an algorithm and simulation technique based on a bivariate kernel density estimation to derive projections of the cumulative likelihood and timing of substitution amongst energy resources and towards solar. In this paper, we apply the methodology to solar PV as an illustration of the technique given multiple sources of uncertainty, and provide a general framework to evaluate investments in competing alternative renewable energy technologies.

We use a real options approach (ROA) which is an application of option valuation techniques originally developed in the finance literature (Black and Scholes, 1973), but which has found important applications in natural resource economics (Arrow and Fisher, 1974; Conrad, 1980; Brennan and Schwartz, 1985), environmental economics (Pindyck, 2000), water economics (Carey and Zilberman, 2002), and most recently in renewable energy economics.

ROA is fundamentally a stochastic dynamic framework analyzing investment decisions in the presence of three factors: uncertainty of the economic environment, irreversibility, and the ability to postpone the investment decision (Dixit and Pindyck, 1994). Traditional static "now or never" net present value (NPV) breakeven models of investment have resulted in predictions that have been observed to overestimate investment and adoption. However, a key result of the real options framework is that the investor will require a significant excess return above the expected present value before making the investment in light of these factors.

Most recently, ROA has found applications in evaluating investments in renewable energy technologies, two notable examples being Lemoine (2010) and Schmit, Luo and Conrad (2011). Lemoine (2010) uses option valuation to compute a more complete market valuation of a plug-in hybrid electric vehicle (PHEV) by incorporating the additional benefit derived from the driver's ability to respond to fuel and electricity prices on a daily basis. Schmit et al. (2011) use the real options framework to evaluate combined entry and exit investment decisions in an ethanol plant.

We extend the current literature both methodologically and empirically. Methodologically, based on Dixit & Pindyck (1994), we incorporate two sources of uncertainty as an extension of the traditional single variable model and provide new analytic insights and comparative static results. While both Lemoine (2010) and Schmit et al. (2011) incorporate two stochastic processes in their analysis, both papers do so in a different framework, and Lemoine examines the valuation but not the threshold of adoption, while Schmit et al. use a numerical approximation procedure to solve the optimal switching problem.

Empirically, to our knowledge, this is the first real options paper to examine the question of solar energy. Further, we develop an algorithm and simulation technique based on a bivariate kernel density estimation, which is essential due to the extension of ROA to incorporate two stochastic processes, and which has general applicability and can be used to evaluate investments in alternative renewable energy technologies.

The results of the model show that if assumptions are maintained, there will be a displacement of incumbent technologies and a widespread shift towards solar PV in the residential and commercial sector in under 30 years, across plausible rates of technological change. Projections consistently indicate that this can occur independent of downstream incentives and carbon pricing policies (at \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2) which generally have a modest impact – and may not be an effective part of climate policy in this regard. Further, both consumer subsidies and carbon taxes become more ineffective with higher rates of technological change, making virtually no difference in certain cases. Results demonstrate that further technological change alone is the crucial determinant and main driver of adoption, outweighing the effect of subsidies and taxes. Suggesting that subsidies and taxes don't make a substantial difference in a technology that's not viable – instead that research does. These results are robust across varying levels of interest rates, technological change, electricity price growth, and incentives.

The results suggest several significant policy conclusions: (i) Concerns regarding recently decreasing consumer subsidies dampening the consumer economics of solar adoption are overstated. (ii) Carbon taxes of \$21/ton CO2 and \$65/ton CO2 have a minor impact in accelerating widespread adoption of solar PV as compared to baseline projections. Carbon pricing at \$21/ton CO2 accelerates adoption by an average of 0-3 years, and pricing at \$65/ton CO2 accelerates adoption by an average of 2-5 years, depending on tech advancement scenario. (iii) A carbon tax of \$150/ton CO2 will have a modest impact on accelerating adoption by an average of 6 - 8 years if the recent higher rates of technological advancement in solar PV are maintained. The impact will be more significant in the scenario with historical lower rates of technological advancement, accelerating adoption by an average of 10.5 to 15.5 years. However projections still indicate a widespread shift towards solar within 26-31 years in this scenario.

Results show that R&D support and technological advancement in solar PV is the crucial determinant in accelerating widespread adoption of solar PV and should play a key role in climate policy. Projections indicate that if recent rates of technological change in solar are maintained, there could be a widespread shift towards solar in 25-28 years *without* any subsidies or carbon pricing.

The paper is organized as follows. Section 2.2 presents the model of the consumer's adoption decision within a stochastic dynamic framework and two sources of uncertainty. Section 2.3 outlines the empirical model, and section 2.4 presents the simulation results and policy implications. Lastly, section 2.5 concludes with a discussion of the main results and limitations of the model.

2.2 The Theoretic Model

We examine the solar PV adoption decision in the residential/commercial sector, driven by the consumer's objective to minimize costs. The consumer weighs the tradeoff between the cost of the solar PV unit versus the long term price of electricity and the potential cost savings that the investment in the solar unit may provide through the value of the displaced electricity.

We abstract from other factors that may motivate the decision to invest in renewable technologies, including energy security concerns, climate change objectives and a general higher willingness to pay for such. Instead we focus on the basic objective of cost minimization, since it is crucial to consider the situation where the solar PV unit pays for itself as that would have a substantial impact on adoption by individual households/enterprises.

We extend ROA to model the investment decision under uncertainty given two stochastic processes – the price of electricity, and the cost of the solar PV unit. Based on this methodology, a threshold decision rule influenced by the individual drift and volatilities of these two processes is developed.

2.2.1The Value of a Live Project

The risk neutral consumer's decision to invest in the modern solar technology depends on the tradeoff between the expected present value of the investment and the fixed cost of the investment, represented by the levelized cost of solar electricity (LCOE). The value of the investment is given by the expected potential cost savings from adopting solar as well as the potential revenue from exporting solar generated electricity back to the grid⁴, assuming inelastic demand. This is given by:

⁴ Given the parameterized values of asp > asu.

$$V(P) = E \int_0^\infty ((P-C)(asu) + FIT (asp - asu)) e^{-rt} dt \qquad (1)$$

where *P* is the price of electricity⁵, *C* is the levelized cost of solar electricity, *asp* is the average amount of solar electricity produced, *asu* is the average amount of solar electricity used, *FIT* is the feed in tariff for the excess solar electricity exported back to the grid, and *r* is the interest rate.

This model captures the potential cost savings of the solar generated portion of the total bill. During the hours when solar is not available, the household incurs no potential cost savings and uses grid supplied electricity as usual, since we are not adding any assumptions of storage.

We assume that once the consumer has invested in the solar PV unit, she will not compare electricity prices and the levelized cost of solar on a daily basis, and decide whether to use grid or solar generated electricity depending on the prices. This would resemble a valuation similar to McDonald and Siegel (1985) and Lemoine (2010), but in the case of solar with no variable costs incurred on a daily basis, the assumption is that the user will choose to use the already paid for system first.

The long term price of electricity and cost of solar are uncertain, and may be represented by Geometric Brownian Motion (GBM) processes⁶ such that:

$$dP = \alpha_P P dt + \sigma_P P dz_P \qquad (2) dC = \alpha_C C dt + \sigma_C C dz_C \qquad (3)$$

Where α_P and α_C are the drift rates for the price of electricity and cost of solar processes, and σ_P and σ_C are the volatility measures respectively, and dz_P and dz_C are increments of a Wiener processes. $E[P(t)] = P_0 e^{\alpha_P t}$ and $E[C(t)] = C_0 e^{\alpha_C t}$ where $P(0) = P_0$ and $C(0) = C_0$. And $E[dz_P^2] = E[dz_C^2] = dt$ as well as $E[dz_P dz_C] = \gamma dt$, where γ denotes the correlation coefficient between P and C. Notably, technological change and an advancements in solar PV implies that α_C is negative, and an increasing rate of technological change implies α_C will become increasingly negative.

Although the price of electricity and cost of solar are both uncertain, once the investment is made, and the technology is adopted, future evolution of the cost of solar becomes irrelevant. Hence, the value of a live project, once adopted is given by:

$$V(P) = \frac{P * asu}{(r - \alpha_p)} - \frac{C * asu}{(r)} + \frac{FIT (asp - asu)}{(r)}$$
(4)

⁵ Under the assumption of a flat rate tariff structure.

⁶ A discussion of the GBM assumption is included in section III.

In the traditional NPV investment model, the consumer will invest if $V(P) \ge 0$, i.e. if the expected present value is positive⁷. Hence, the threshold price at which adoption occurs is given by:

$$P_{NPV}^{*} = \left(\frac{C * asu - FIT * s}{r}\right) \left(\frac{r - \alpha_{p}}{asu}\right)$$
(5)

where s = (asp - asu), i.e. the difference between the amount of solar electricity produced and used.

Intuitively the consumer is more likely to adopt (i.e. P_{NPV}^* decreases) as the difference between the amount of solar produced and used increases, and as FIT increases due to the revenue potential. She is less likely to adopt the nascent technology as the LCOE and the total life cycle costs of the solar system increase.

However, in practice consumers often require that the investment benefit exceeds the cost by a positive hurdle rate, which is not accounted for in the traditional NPV model, but which will invariably have consequences for the adoption potential of a technology.

2.2.2 The Value of the Option to Invest

When considering the value of the option to invest, the consumer will have to consider both the price of electricity and the cost of solar as random variables, i.e. they have the option to invest if the price of electricity should rise in the future and/or the cost of solar PV should fall.

This yields a dynamic programming problem, and specifically an optimal stopping problem where the option to invest is a function of both these variables, i.e. F(P, C) and where one has to find the region of values of (P, C) where investment will occur, not occur and the critical boundary that separates these two regions. In the continuation region in which it is optimal to hold onto its option to invest, the Bellman equation is given by:

$$rFdt = E[dF]$$
 where $F(P,C)$ (6)

since there is no current period payout from holding the option. Equation (6) states that over the interval dt, the return of the investment opportunity is equal to its expected rate of capital appreciation.

Using Ito's lemma to expand dF, yields:

$$dF = F_P dP + F_C dC + \frac{1}{2} (F_{PP} (dP)^2 + 2F_{PC} dP dC + F_{CC} (dC)^2)$$
(7)

⁷ As the levelized cost of electricity from solar includes the total life cycle costs (TLCC) of the system.

Which, substituting for *dP* and *dC* and rearranging, yields:

$$E[dF] = \alpha_P PF_P dt + \alpha_C CF_C dt + \frac{1}{2} (F_{PP} \sigma_P^2 P^2 + 2F_{PC} \gamma \sigma_P \sigma_C PC + F_{CC} \sigma_C^2 C^2) dt$$
(8)

Where $E[dz_P] = E[dz_C] = 0$ and where γ is the correlation coefficient between P and C. Given (8) the Bellman equation now becomes:

$$\alpha_P P F_P + \alpha_C C F_C + \frac{1}{2} (F_{PP} \sigma_P^2 P^2 + 2F_{PC} \gamma \sigma_P \sigma_C P C + F_{CC} \sigma_C^2 C^2) - rF = 0$$
(9)

Which applies over the region of (P, C) space where it is optimal to leave the option unexercised.

Over the region where the option is immediately exercised, we have the relevant value matching and smooth pasting conditions. However the boundary is itself unknown, and must be determined together with the solution for the function satisfying (9).

Consistent with Dixit & Pindyck (1994), since the option function is homogeneous of degree 1 in P and C, the optimal decision should therefore depend only on the ratio $k\equiv P/C$, enabling us to write:

$$F(P,C) = Cf(\frac{P}{C}) = Cf(k) \quad (10)$$

Where f(k) is now the function to be determined. The corresponding partials are given by: $E_{k}(B_{k}C) = f'(k)$

$$F_{P}(P, C) = f(k)$$

$$F_{C}(P, C) = f(k) - kf'(k)$$

$$F_{PP}(P, C) = f''(k)/C$$

$$F_{PC}(P, C) = -kf''(k)/C$$

$$F_{CC}(P, C) = k^{2}f''(k)/C$$

And substituting these in the Bellman equation (9) yields:

$$\frac{1}{2}(\sigma_{\rm P}^2 - 2\gamma\sigma_P\sigma_C + \sigma_{\rm C}^2)k^2f''(k) + (\delta_C - \delta_P)kf'(k) - \delta_Cf(k) = 0 \quad (11)$$

where $\delta_P = (r - \alpha_{\rm P})$ and $\delta_C = (r - \alpha_{\rm C})$

The solution for f(k) subject to the relevant boundary conditions:

$$f(0) = 0 \qquad (12a)$$

$$f(k) = \frac{k * asu}{(r - \alpha_{\rm P})} - \frac{asu}{r} + \frac{FIT * s}{C * r}$$
(12b)⁸
$$f'(k) = \frac{asu}{(r - \alpha_{\rm P})}$$
(12c)⁹

has the following form analogous to the one variable case:

$$f(k) = A_1 k^{\beta_1}$$
(13)
where $\beta_1 = \frac{1}{2} - (\delta_C - \delta_P) / \sigma^2 + \{ [\frac{(\delta_C - \delta_P)}{\sigma^2} - \frac{1}{2}]^2 + [(2\delta_C) / \sigma^2] \}^{1/2}$
and $\sigma^2 = (\sigma_P^2 - 2\gamma \sigma_P \sigma_C + \sigma_C^2)$.

Solving these equations yields the optimal investment threshold value k^* and P^*_{ROA} :

$$k^* \equiv P/C = \left(\frac{\beta_1}{\beta_1 - 1}\right) \left(\frac{asu}{r} - \frac{FIT * s}{Cr}\right) \left(\frac{r - \alpha_p}{asu}\right)$$
(14)
$$P_{ROA}^* = \left(\frac{\beta_1}{\beta_1 - 1}\right) \left(\frac{C * asu - FIT * s}{r}\right) \left(\frac{r - \alpha_p}{asu}\right) = \left(\frac{\beta_1}{\beta_1 - 1}\right) P_{NPV}^*$$
(15)

For $P < P_{ROA}^*$ the household holds onto its option to invest and for $P \ge P_{ROA}^*$ the household exercises its option and invests in solar PV. Since $\beta_1 > 1$, and since $P_{ROA}^* = \left(\frac{\beta_1}{\beta_1 - 1}\right)P_{NPV}^*$, hence $P_{ROA}^* > P_{NPV}^*$. Thus, when accounting for irreversibility, uncertainty and the ability to wait, the household requires a higher price than given by the standard NPV rule before they are willing to invest.

While a key result of the real options model has been to illustrate the effect of increased uncertainty on delaying investments, we extend the analysis to illustrate two significant dynamics that emerge - providing further insight into the differing paradigms of the NPV and ROA models of investment.

⁸The value matching condition.

⁹The relevant smooth pasting condition.

2.2.3 Proposition 1 A higher rate of technological change in the nascent technology <u>delays</u> adoption in ROA - resulting in an increase the k* threshold by increasing the excess return required by the consumer before she is willing to give up the option to invest.

This is illustrated in fig. 2.1 in terms of the k* threshold ratio, indicating that the consumer will adopt later, at a higher price of electricity for a given cost of solar, i.e. she demands a higher premium before adopting the nascent technology.



Fig. 2.1: K* Separating Region of Adoption and Waiting

This is a counterintuitive result of increased funding, R&D productivity and technological change, which are ultimately intended to promote adoption. On one hand, the asset has become cheaper – hence one would expect the consumer to be more likely to adopt the technology, and adopt it sooner. However, if the rate of cost decline increases, waiting instantly becomes more valuable and giving up the option to wait becomes more costly, hence the user will require a higher premium to give up this option. This is entirely consistent with the energy efficiency gap observed in consumer behavior.

This captures the essence of ROA, i.e. the tradeoff between immediate payoff, versus capital appreciation and the payoff associated with such. Postponing the investment entails giving up immediate payoff for the benefit of capital appreciation. And with the increased capital appreciation, giving up the option to invest becomes more costly.

Specifically, this effect is driven by the term $(\alpha_P - \alpha_C)$ the equation for β : ¹⁰

¹⁰The term $(r - \alpha_c)$ encourages adoption unambiguously by discounting the cost of solar more in present value terms.

$$\beta = \frac{1}{2} - (\alpha_P - \alpha_C)/\sigma^2 + \{ \frac{(\alpha_P - \alpha_C)}{\sigma^2} - \frac{1}{2} \}^2 + \frac{[2(r - \alpha_C)/\sigma^2]}{(\alpha_P - \alpha_C)/\sigma^2} \}^{1/2}$$
delay adopt sooner¹¹

The term $(\alpha_P - \alpha_C)$ represents the wedge between the price of electricity and cost of solar as illustrated in figure 2. An increase in this wedge essentially lends value to both the adoption of the asset, as well as to the value to waiting. The net effect is the one that dominates between the two. The condition for $\alpha_{\mathcal{C}} \downarrow => \beta \downarrow$ is evident given the comparative statics for beta 12 .

$$\frac{\partial \beta}{\partial \alpha_c} = \frac{1}{\sigma^2} - \frac{1}{\sigma^2} \left[\frac{(\alpha_P - \alpha_C)}{\sigma^2} + \frac{1}{2} \right] + \frac{1}{2} \left[\frac{(\alpha_P - \alpha_C)}{\sigma^2} - \frac{1}{2} \right]^2 + \left[2(r - \alpha_C)/\sigma^2 \right] \right]^{1/2}$$
Where $\frac{\partial \beta}{\partial \alpha_c} > 0$ iff $r > \alpha_P$
And $\frac{\partial \beta}{\partial \alpha_c} \le 0$ iff $r \le \alpha_P$

given that β is the positive root of the fundamental quadratic

The relationship between r and α_P determines the switching condition independent of the relative magnitudes of α_P versus α_C , i.e. the rate of increase in price of electricity versus the rate of decrease in cost of solar. Intuitively, this result signifies that one will postpone to reap the benefits of further technological change in solar as long as it isn't prohibitively expensive to do so, i.e. as long as the price of electricity is not increasing at an increasing rate (in present value terms) while postponing the investment¹³.

By comparison, the NPV threshold of investment remains unchanged irrespective of the rate of technological change, since it is a static "now or never" proposition and doesn't consider the option of postponing the investment decision and further technological change in the nascent technology.

¹¹ If $\frac{(\alpha_P - \alpha_C)}{\sigma^2} > \frac{1}{2}$. ¹²Unambiguously $\beta \downarrow => (\frac{\beta}{\beta - 1}) \uparrow$ given beta is the positive root of the fundamental quadratic.

¹³ One will postpone adoption if the price of electricity and cost of solar are both decreasing at a decreasing rate. Irrespective of the relative magnitudes of the rates of change and by virtue of their signs, the rate of decay of the cost of solar is greater than that of the price of electricity, in present value terms.

2.2.4 Proposition 2 An increase in the interest rate <u>encourages</u> adoption in ROA - resulting in a lower k* threshold.

This is a counterintuitive result, and contrary to the standard NPV calculation in which an increase in the interest rate delays adoption, by discounting the future value of the investment at a higher rate and breaking even later.

$$r \uparrow => P_{NPV}^* \uparrow$$

 $r \uparrow => k^* \downarrow$

The comparative statics illustrate that β will always increase with an increase in the interest rate, implying a decrease in the hurdle rate¹⁴.

$$\frac{\partial \beta}{\partial r} = \frac{1}{\sigma^2} \frac{1}{\left\{ \left[\frac{(\alpha_P - \alpha_C)}{\sigma^2} - \frac{1}{2} \right]^2 + \left[2(r - \alpha_C)/\sigma^2 \right] \right\}^{1/2}} > 0$$
$$r \uparrow => \beta \uparrow => \left(\frac{\beta}{\beta - 1} \right) \downarrow$$

However, the key lies in recognizing that k* is composed of two opposing dynamics, which would further indicate that *ROA* <u>should not</u> be as sensitive to the interest rate as *NPV*.

$$k^* = \frac{\left(\frac{\beta}{\beta-1}\right) \downarrow P^*_{NPV} \uparrow}{C}$$

Intuitively, the hurdle rate always decreases with an increase in the interest rate because a higher interest rate implies that the current loss from postponing increases, while the future gain from postponing decreases. The net effect is a decrease in k*.

If however, the rate of technological change in solar were extremely low, such that the gain from postponing decreases further, this effect would drive down the hurdle rate further (consistent with Proposition 1) and k* could *increase* with an increase in the interest rate – in which case the NPV effect would dominate, and ROA would approach NPV.

$$k^* = \frac{\left(\frac{\beta}{\beta-1}\right) \downarrow \downarrow \quad P^*_{NPV} \uparrow}{C}$$

¹⁴ The hurdle rate is given by the expression $\left(\frac{\beta}{\beta-1}\right)$, and is defined as the excess return required above the standard NPV calculation which determines the optimal investment threshold in ROA, as illustrated in equation (15).

$$r \uparrow => k^* \uparrow$$

 $P^*_{ROA} \rightarrow P^*_{NPV}$

Similarly, if uncertainty were to tend to zero, ROA would approach NPV

$$\sigma^2 \to 0 \implies (\frac{\beta}{\beta - 1}) \to 0$$
$$P^*_{ROA} \to P^*_{NPV}$$

illustrating that without option value, the mean effect is significant. With option value, both the mean and variance effects are significant. In the NPV scenario, a high interest rate reduces future value making adoption less likely. While in ROA, a high interest rate reduces the cost of high variance in the future, making adoption more likely¹⁵. In ROA the variance effect dominates - illustrating the differing paradigm of the two investment rules.

2.3 Empirical Model

The long term price of electricity and the cost of the solar PV unit are assumed to be uncertain, while all other inputs are modeled deterministically. The model is evaluated with a flat rate tariff structure for the price of electricity rather than time of use/real time pricing tariff rate structures. While there are numerous papers discussing the economics of solar PV with different tariff rate structures (Borenstein, 2007), we abstract from such issues and consider the base case of flat rate structure.

Price of Electricity

There have been numerous studies examining prices in electricity markets and the stochastic processes they may follow (Deng, 2000). Some studies contend that electricity price data might not be well represented by traditional commodity price models of GBM due to the fact that on-peak electricity spot prices are highly volatile and strongly mean reverting, while GBM does not capture this dynamic.¹⁶

However, Schwartz and Smith (2000) and Pindyck (2001) contend that for considerations of long term investment decisions, the long term factor is the decisive one, and GBM

¹⁵ Given the assumptions of GBM, the mean grows linearly with time, while the variance grows at a quadratic rate.

¹⁶ Suggesting that combining a jump process with mean reversion can capture the salient features of daily electricity spot prices where GBM can't.

assumptions are appropriate even if they might ignore short term mean reversion in the price dynamics.

Consistent with this, we model the long-term electricity price process as a GBM process with the parameters based on futures contracts for PJM Interconnection Electricity Futures traded on the NYMEX¹⁷.

The annual growth rate of the long term price of electricity is estimated from PJM electricity futures contracts for four consecutive years 2014-2017. Consistent with Fleten (2007), according to the GBM process the expected price of electricity evolves according to $E[P(t)] = P_0 e^{\alpha_P t}$ where α_P represents the annual rate of growth in the price of electricity, estimated as 2.89% using an exponential regression.

The annual historic volatility, which is a measure of the variance of the price distribution, is estimated using daily historical futures price changes of the daily prices of one-month ahead PJM electricity futures contracts traded three years in advance at the NYMEX. We have used prices for the trading period March 2009 – Feb 2013, such that the prices are for futures contracts delivery in March 2012 – Feb 2016. The resulting annual volatility was estimated as $\sigma = 14.09\%$.

In addition, as the future evolution of the price of electricity is crucial to the results, we also conduct simulations with electricity price parameters based on historical EIA average real residential and commercial electricity prices, for the years 1990 - 2002 and 2003 - 2009, resulting in much lower annual electricity growth rates of -0.2479% and 0.2011% respectively¹⁸. We discuss these results in addition to the results based on futures estimates, and present details in Appendix A.

Cost of Solar

Estimates of plausible rates of technological advancement in solar PV are based on historic installed cost data in the US (Barbose et al., 2012) as well as on expert elicitation (Rausser et al., 2010) to explore the possible link between R&D funding levels and technological advancement in solar, at two different levels.

Historic installed prices of solar PV units (≤ 10 kW) have exhibited a dramatic decline in costs in recent years in the US, driven primarily by falling module costs. Recent estimates of price declines for the period 2008-2011 indicate a decline of -11.20% per year, while the period 2009-2011 indicates an even higher decline of -14.20% per year.

¹⁷ The PJM Interconnection, LLC, administers the largest electricity market in the world serving more than 44 million customers in the US.

¹⁸ The estimated real annual electricity growth rate for the time period 1990 - 2012 was 0%.

Notwithstanding this recent precipitous decline in prices, we base our estimate of the long term historic rate of price declines on average declines exhibited during the period 1998-2011, corresponding with an annual growth rate of -4.41% in the cost of solar. And we base our estimates of the recent higher rate of cost declines observed during the years 2007-2011 as - 9.30%, thereby adopting a more conservative view of rates that could plausibly be maintained in the future.

In addition, we perform expert elicitation to capture the possible impact of a modest increase in R&D spending levels on the corresponding rate of technological change, as an indication of optimal R&D funding levels.

Public R&D funding for solar has in general remained flat for the past two decades (mid 1980's – 2008) at an average level of \$115 million per year. There has however been a recent spike in general R&D funding for renewable energy due to the Recovery Act in 2009, and an associated increase in solar funding at \$417 million in 2009, \$359 million in 2010, and \$403 million in 2011.

We performed expert elicitation based on a random sample of renewable-energy experts working on technical/scientific breakthroughs in solar PV, drawing from public, private, and academic research institutions. Probability distributions of future costs were elicited for two scenarios: (i) A public R&D funding level of \$115 million per year as a representation of baseline historic R&D funding levels. (ii) A scenario with a 50% increase in R&D spending levels corresponding with a funding level of \$173 million per year.

The elicited estimates were fitted to a distribution using R/SHELF software and aggregated using a linear pool. Linear regressions were fitted to obtain estimates of annual drift rates for baseline/status quo funding scenario as well as increased funding scenarios. The results were $\alpha_{CSQ} = -0.044/\text{yr}$ (a growth rate of -4.4% annually) for status quo funding, corresponding very closely with the historic rate of price declines based on Barbose et al. (2012), and $\alpha_{CIN} = -0.0563/\text{yr}$ (a growth rate of -5.63% annually) for the increased funding scenario.

Investment Cost

The current investment cost of a 10kW DC solar PV system¹⁹ and corresponding levelized cost of electricity (LCOE) are based on California Energy Commission estimates.

Table 2.1 presents the average installed price of solar PV (\$2012) given differing discount rates, including installation and replacement of inverters over the assumed 25 year lifetime of the solar unit, assuming a 1% aging factor per year in the output of the

¹⁹ Corresponding with a large residential and small commercial system.

PV unit. Current average retail inverter cost for a 10kW system lies at approx. \$7120, and we assume that costs will decline by 2% per year, consistent with Wiser et al., (2006) and Borenstein (2008).

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Table 2.1 - Investment Cost and LCOE for a 10kW Solar PV Installation				
Annual Real Interest Rate	3%	5%		
Cost of PV Installation	\$56,000	\$56,000		
Inverter replacement cost (8 yrs)	\$6057	\$6057		
Inverter replacement cost (16 yrs)	\$5153	\$5153		
Discounted Present Cost	\$63,993	\$62,460		
Levelized Cost (per MWh)	\$295	\$353		

Average Amount Produced

The parameter for average amount of solar electricity produced is based on estimates provided by Borenstein (2008). The data is based on TRNSYS simulations for production from a 10kW (DC) solar PV installation in San Francisco, Sacramento, and Los Angeles over the course of one year, in conjunction with weather data from the U.S. National Renewable Energy Laboratory (NREL), assuming the panels were mounted at a 30 degree tilt facing different directions, and a 16% derate conversion factor. The TRNSYS model produced hourly simulated production data for one year, resulting in averages that ranged from 1.349 -1.650 (kWh/hr – AC). We use an estimate of 1.499 kWh/hr, representing an annual 13139 kWh of solar electricity produced.

Average Amount Used

One would ideally base the parameter for average amount of solar PV used on real usage patterns of households with installed solar PV units. However absent such detailed data, a next best estimation is made based on the fact that demand peaks at hours during the day and seasons during the year when solar production peaks.

Hence, given the broad overlap, we base our parameters on average U.S. household consumption. EIA estimates for the average annual electricity consumption for a U.S. residential utility household in 2011 was 11,280 kWh, averaging 940 kWh per month. Louisiana had the highest annual consumption at 16,176 kWh and Maine the lowest at 6,252 kWh.

Solar Feed in Tariff Rates

The parameter used for the FIT rates are based on the CA PUC for different renewable energy technologies, including Solar. Feed-in tariffs are closely associated with solar PV panels, designed to encourage the adoption of renewable energy technologies. Under the feed-in-tariff, regional or national electric grid utilities are obliged to buy electricity generated from renewable energy sources and pay a guaranteed purchase price set in a long-term (10–25 year) contract. As of 2009, FIT policies have been enacted in sixty three countries, including over a dozen states in the United States.

We base our FIT parameter on the CA PUC rates effective January 2012, which range from \$0.07688/kWh - \$0.12326/kWh, depending on the contract start date and the length of the contract. We use an estimate of \$0.097412/kWh as a baseline parameter, representing the average rate for a 25 year contract, ignoring time of delivery (TOD) adjustment factors.

Average Historic Consumer Subsidies

Incentives to the residential and commercial sector (which have historically accounted for approximately 70% of solar generation) have ranged from up-front cash rebates, to renewable portfolio standards, and federal and state tax benefits. Incentives have coved an estimated 3% - 50% of total system cost (Peterson, 2011), ranging from \$500 - \$22,000 per installation in the states surveyed, averaging at \$14500 per installation.

Carbon Taxes

Carbon taxes remain controversial and surrounded by considerable uncertainty, and to date have not been enacted in the US on a national scale.

Aside from controversy regarding efficacy, growth and distributional effects, estimates of the of the social cost of carbon (SCC) themselves remain highly uncertain due to the underlying uncertainties in the science of climate change science, choice of discount rates, and valuation of economic impacts (Pindyck, 2013).

Current US government and NBER estimates set the SCC for 2010 at \$21/ton CO2 (\$2007) and \$65/ton CO2 (\$2007) representing estimates of "most likely" scenario and "potential higher-than expected" impacts respectively (Greenstone et al., 2011; Interagency Working Group, 2010). However, there is considerable disagreement regarding these estimates.

Pindyck (2013) asserts that while \$21/ton CO2 or \$65/ton CO2 estimates might provide a reasonable estimate of "most likely outcomes" and plausible events, they fail to assess more extreme outcomes and capture the possibility of catastrophic climate outcomes - which should be of major concern, and which might lead to a SCC as high as \$100-\$200/ton CO2.

Given the debate regarding the correct SCC, we measure the impact of carbon pricing policies at \$21, \$65 and \$150/ton CO2.

We estimate the threshold of adoption under both the standard NPV investment rule as well as the ROA rule for various funding and technological advancement trajectories for

a representative 10kW solar PV system, and examine the sensitivity of the hurdle rate and threshold of investment to uncertainty and correlation parameters.

Based on the results and parameters from the previous two sections (table 2.2), we illustrate how the price of electricity at which adoption of solar PV will occur exceeds that of the standard NPV calculation by a positive hurdle rate, which captures the excess return the consumer will require before making the irreversible investment:

$$P_{ROA}^* = \left(\frac{\beta_1}{\beta_1 - 1}\right) P_{NPV}^* \quad (15)$$

Consistent with propositions 1 and 2, we illustrate how (i) Increased R&D funding and technological advancement in solar PV will lead to *delayed* adoption. (ii) An increase in the interest rate will *encourage* adoption in the ROA model.

Table 2.2 - Baseline Parameter Values (r = 3%)

Baseline Parameter Values	
C = \$0.295/kWh	P0 = \$ 0.1162/kWh
FIT = \$0.097412/kWh	$\gamma = 0$
asp = 13136 kWh/yr	asu = 11280 kWh/yr
$\alpha_P = + 0.0289/\text{yr}$	$\sigma_P = 0.1409/\text{yr}$
α_{CSQ} = - 0.0441/yr	$\sigma_{CSQ} = 0.1409/\text{yr}$
$\alpha_{C 50\% Incr} = - 0.0563/yr$	$\sigma_{C 50\% Incr} = 0.1409/\text{yr}$
$\alpha_{C High}$ = - 0.093/yr	$\sigma_{C High} = 0.1409/\text{yr}$

Note: P0 is based on EIA "Electric Power Monthly Feb 2013" average retail price to residential consumers.

The baseline results are illustrated in tables 2.3 and 2.4 for r = 3% and 5% respectively, including the main result of the ROA k* threshold ratio - the constant ratio of P/C which separates the waiting region and adoption region (see fig. 2.1).

α _c	β	Hurdle Rate $\left(\frac{\beta}{\beta-1}\right)$	$\mathbf{P}_{\mathrm{ROA}}^{*} = \left(\frac{\beta}{\beta-1}\right) \mathbf{P}_{\mathrm{NPV}}^{*}$	k *
-0.0441	1.012	85.62	\$0.876/kWh	2.97
-0.0563	1.0104	96.69	\$ 0.989/kWh	3.35
-0.093	1.0078	130.00	\$ 1.3298/kWh	4.51

Note: Drift rates α_c are presented on annual basis. P*npv = 0.0102/kWh, C = 0.295/kWh.

α _c	β	Hurdle Rate $\left(\frac{\beta}{\beta-1}\right)$	$P_{ROA}^* = \left(\frac{\beta}{\beta - 1}\right) P_{NPV}^*$	k^*
-0.0441	1.2172	5.6049	\$0.797/kWh	2.258
-0.0563	1.1938	6.1611	\$0.8761/kWh	2.482
-0.093	1.1459	7.855	\$ 1.1171/kWh	3.164

Table 2.4 - ROA Results for Baseline Parameters (r = 5%)

Note: Drift rates α_c are presented on annual basis. P*npv = \$0.142/kWh, C = \$0.353/kWh.

In the baseline, the threshold price of adoption given by the standard NPV investment rule is P^* electricity = 0.0102/kWh for r=3%, and 0.142/kWh for r= 5% (while LCOE from solar is \$0.295/kWh and \$0.353/kWh respectively) indicating the extreme sensitivity of NPV to interest rate assumptions. Furthermore, the NPV calculation remains the same between all three technological change scenarios since NPV is essentially a static, "now or never" calculation - which doesn't incorporate the dynamic features of ROA.

The corresponding ROA threshold calculations are dependent on the rate of technological change in solar. The hurdle rate across all scenarios is significant, illustrating the large discrepancy between the two investment rules, i.e. by failing to account for the influence of uncertainty and irreversibility the NPV rule is biased in favor of early investment.

Consistent with proposition 1, an increase in the rate of technological change results in a higher k*, indicating delayed adoption. Consistent with proposition 2, and contrary to the standard NPV result, an increase in the interest rate (for a given level of technological change) results in a lower k* threshold – thereby encouraging adoption in the sense that ROA is approaching NPV.

Most importantly, given the P*roa and k* threshold results, for every price of electricity one can calculate the corresponding level of the cost of solar that will trigger adoption as illustrated in tables 2.5 and 2.6 for the historic lower rate of technological advancement and recent higher average cost decline scenarios respectively.

(β)	$K^* = P/C$	P Electricity (\$/kWh)	C Solar (\$/kWh)
$\left(\frac{r}{\beta-1}\right)$			
85.62	2.97	0.876	0.295
85.62	2.97	0.743	0.25
85.62	2.97	0.594	0.20
85.62	2.97	0.297	0.10
85.62	2.97	0.149	0.05

1 ubic 2.0	The shold of Adoption for Recent Higher Rate of Teenhear Change $(1 - 5/6)$			
$\left(\frac{\beta}{\beta-1}\right)$	$K^* = P/C$	P Electricity (\$/kWh)	C Solar (\$/kWh)	
130	4.51	1.330	0.295	
130	4.51	1.128	0.25	
130	4.51	0.902	0.20	
130	4.51	0.451	0.10	
130	4.51	0.226	0.05	

Table 2.6 – Threshold of Adoption for Recent Higher Rate of Technical Change (r = 3%)

Robustness Analysis

The sensitivity of P* roa and the k* threshold to uncertainty and correlation parameters are as anticipated (see table 7). A decrease (increase) in uncertainty, i.e. in σ_C or σ_P parameters, reduces (increases) the k* threshold ratio as compared to baseline values, implying sooner (delayed) adoption. ROA illustrates that uncertainty can have impact on investment independent even under risk neutrality.

A positive correlation of 0.3 between the price of electricity and cost of solar instead of the baseline assumption of no correlation, results in earlier adoption and a lower hurdle rate and k* threshold ratio, given the covariance of the variables. Correspondingly, a negative correlation of -0.3 between the price of electricity and cost of solar, results in delayed adoption and a higher hurdle rate and k* threshold.

Table 2.7 - Robustness Analysis Results (r=3%)				
Parameter	Value (old \rightarrow new)	Hurdle Rate $\left(\frac{\beta}{\beta-1}\right)$	k *	
σ_{C} or $\sigma_{P}(\downarrow)$	0.1409 → 0.10	81, 92, 125	2.812, 3.196, 4.35	
σ_C or σ_P (\uparrow)	0.1409 → 0.20	94, 105, 139	3.29, 3.67, 4.82	
γ (↑)	0 → 0.30	80, 91, 124	2.77, 3.16, 4.32	
γ (↓)	0 → - 0.30	91, 102, 135	3.16, 3.54, 4.69	
Baseline Values		85.62, 96.69, 130	2.97, 3.35, 4.5	

Note: All else constant at baseline values. Hurdle rate and k* are presented for three technological change scenarios (i.e. $\alpha_c = -0.0441$, -0.0563 and -0.093) respectively.
2.4 Results and Implications



Fig. 2.2: Single Realization of GBM Stochastic Processes for the Price of Electricity and Cost of Solar

For illustrative purposes, we include figure 2.2 to show a single realization of the stochastic GBM price processes over 50 years, for the base case scenario free of any incentives or carbon pricing. In this realization, the price of electricity and the cost of solar for two alternative technological change assumptions are shown, together with the corresponding deterministic trend lines.

The relevant baseline k* threshold values of 2.97 and 3.35 for the respective trajectories can be seen as the ratio required between the price of electricity and cost of solar at a given time that will trigger adoption, thus translating the analytic results of the previous section into a threshold measure of time.

We base our results on 1000 realizations of each GBM stochastic price process, and develop an algorithm and simulation model based on a bivariate kernel density estimation to assess the joint distribution of the price and cost realizations, and corresponding k* distribution at each time step. This is crucial, as the extension of ROA to incorporate two stochastic processes renders the k* threshold of adoption as a ratio two unknown distributions at each time step.

Given the random nature of the distribution of prices, our analysis allows us to estimate the cumulative distribution of adoption (figures 2.3 - 2.5) as a function of various policy parameters, which has previously not been done with the real options approach. These estimates provide key information to assess the net social benefit from investments in R&D and consumer subsidies.



Fig. 2.3: Cumulative Likelihood and Timing of Adoption Historic Lower rate of Technological Change in Solar Energy (r= 3%, $\alpha_c = -0.048$)



Fig. 2.4: Cumulative Likelihood and Timing of Adoption 50% Increased Funding and Technological Change in Solar Energy (r= 3%, $\alpha_c = -0.056$)



Fig. 2.5: Cumulative Likelihood and Timing of Adoption Recent Higher Rate of Technological Change in Solar Energy (r= 3%, $\alpha_c = -0.093$)

We analyze the following scenarios based on baseline parameter values (table 2.2): (i) Baseline results for alternative solar R&D funding and technological change scenarios without consumer incentives or carbon pricing. This includes three technological change scenarios - a historic lower technological advancement in solar scenario corresponding with status quo R&D funding, a 50% increase in R&D funding corresponding with a modest increase in technological advancement as based on expert elicitation, and a third scenario corresponding with recent higher rates of technological advancement reflecting average cost declines observed during 2007-2011. (ii) The impact of historic average consumer subsidies of \$14500 given alternative assumptions of technological change. (iii) The impact of \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2 carbon pricing given alternative assumptions of technological change.

In addition, we perform simulations for alternative electricity price parameters of -0.2479% and +0.2011% based on EIA historical average residential and commercial electricity prices (for the years 1990-2002 and 2003-2009 respectively). The results for these simulations are presented in Appendix A, however in general they indicate the following: (i) As expected, a low or negative evolution of the price of electricity delays adoption considerably. (ii) Both consumer subsidies and carbon taxes display a modest increase in impact with lower growth rates of electricity prices. (iii) However, results remain consistent across all scenarios of differing electricity price trajectories with overall results demonstrating that further technological change is the crucial determinant and main driver of adoption.

PELEC +2.89%	BASELINE			AV. CONSUMER INCENTIVES		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	13y 9m	13y 5m	12y 1m	10y 11m	10y 10m	10y 4m
40%	23y 9m	22y 0m	18y 7m	20y 3m	18y 10m	16y 2m
50%	27y 3m	25y 1m	20y 4m	23y 5m	21y 4m	17y 9m
60%	31y 9m	28y 3m	22y 6m	27y 3m	24y 0m	19y 6m
70%	36y 7m	32y 4m	24y 11m	31y 10m	27y 8m	21y 8m
80%	45y 8m	39y 6m	28y 2m	40y 2m	33y 4m	24y 8m
90%	Not within 50 years	Not within 50 years	34y 2m	Not within 50 years	43y 4m	29y 4m

Table 2.8 – Baseline Results for Likelihood and Timing of Adoption & Impact of Average Historic Consumer Incentives (pelec = +2.89%, r=3%)

*Base Case*²⁰: Results for the cumulative likelihood and timing of adoption for the average consumer are shown in table 2.8 across alternative R&D and technological advancement scenarios in solar.

Independent of any incentives or carbon pricing, projections indicate that if historic lower technological change rates are maintained, there is a 70% likelihood of adoption within approx. 37 years, and a 80% likelihood within approx. 46 years. However, if the higher average cost declines observed within the recent years are maintained, it would accelerate adoption considerably, resulting in a 70% likelihood of adoption within 25 years, and a 80% likelihood within 28 years. In this latter scenario, under an entirely plausible rate of technological change, projections indicate that there could be a widespread shift towards solar in under 30 years in the residential and commercial sector – without any incentives or carbon pricing.

This result is consistent with Chakravorty et al. (1997) who show an endogenous substitution amongst energy sources and a shift towards solar energy across all sectors in 52 - 92 years²¹ and the subsequent implications for global warming. They use an optimal control framework, without uncertainty, to simulate an economy wide energy demand model with multiple exhaustible resources and multiple demand sectors with solar as the representative and most likely backstop technology across all sectors, including transportation. While they acknowledge that a mix of technologies may eventually dominate, our results indicate a dominant role for solar in the residential and commercial sector, and solar as a viable part of our future energy mix plausibly in under 30 years.

Results based on expert elicitation (Rausser et al., 2010) suggest that a \$60 million increase over historic status quo funding levels of \$115 million/year may accelerate adoption by approx. 5-6 years on average as compared to baseline results. This suggests policy conclusions about levels of R&D funding that may be necessary to attain desired levels of adoption, and that a modest increase of \$60 million may not be enough to accelerate adoption at a significant rate.

Average Historic Consumer Incentives: Recent cost declines in solar PV have been accompanied with declining consumer incentives across most states - which many fear will dampen the overall consumer economics of solar adoption. Our results strongly suggest that these concerns are overstated.

Results indicate (table 2.8) that if recent cost declines are maintained, average historic consumer incentives have a minimal impact of accelerating adoption by approximately 3 years as compared to the base case scenario, i.e. a widespread shift would be observed with 70% likelihood within 22 years, and 80% likelihood within 25 years.

²⁰ We present the simulation results for r = 3%. However, consistent with the analytical results which illustrate the relative insensitivity of ROA to interest rate changes, the simulation results are very similar across r = 3% and 5%, exhibiting the same key dynamics.

²¹ By 2065 – 2105, depending on technological change scenario.

In the scenario with the lower historic rate of technological advancement, projections indicate a slightly higher impact of consumer incentives, accelerating adoption by an approximately 5-6 years as compared to the base case, albeit with widespread adoption still occurring only within 32 - 40 years.

In general, the results indicate a difference of 3-6 years depending on cost decline scenarios - strongly suggesting the policy conclusion that average historic incentives have a modest impact in encouraging adoption of solar technologies, and virtually no impact if the recent higher cost declines are maintained.

PELEC +2.89% CO2 Tax (\$21/ton CO2)	COAL			NATURAL GAS		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	12y 3m	12y 2m	11y 2m	12y 11m	12y 5m	11y 7m
40%	22y 3m	21y 5m	17y 0m	23y 4m	20y 10m	17y 5m
50%	25y 1m	24y 3m	18y 10m	27y 2m	24y 1m	19y 2m
60%	29y 4m	27y 7m	20y 11m	31y 9m	27y 6m	21y 2m
70%	34y 5m	31y 8m	23y 0m	36y 5m	31y 9m	24y 6m
80%	42y 11m	39y 1m	25y 9m	45y 11m	38y 3m	26y 11m
90%	Not within 50 years	Not within 50 years	31y 4m	Not within 50 years	Not withir 50 years	n 32y 1m

Table 2.9 – Impact of 21/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = +2.89%, r=3%)

Carbon Taxes At \$21/ton CO2 and \$65/ton CO2: Results for a carbon tax of \$21/ton CO2 and \$65/ton CO2, representing SCC estimates for "most likely" and "higher-than expected" impact scenarios are shown in tables 2.9 and 2.10 respectively.

Projections indicate that a \$21/ton CO2 carbon tax accelerates adoption by an average of 0-3 years, with a consistently lower impact in the scenario with the higher rate of technological advancement. The carbon tax would accelerate adoption by 2-3 years if the source of electricity were derived from coal, and by 0-1 years if derived from natural gas.

Projections strongly suggest the policy conclusion that while this may be the most feasible level of carbon pricing, it is also the most ineffective and has a modest impact in accelerating adoption. Notwithstanding growth and distributional effects - a carbon tax of \$21/ton CO2 would raise the price of a gallon of gasoline by \$0.19 and a barrel of crude oil by \$9.03.

Projections for carbon pricing at \$65/ton CO2 in general indicate an acceleration of adoption by an average of 2-5 years, once again with a consistently lower impact in the scenario with the higher rate of technological advancement.

Specifically, if the recent average cost declines in solar are maintained, results indicate that a widespread shift would be observed with 70% likelihood within 21 years (22 years if natural gas), and 80% likelihood within 23 years (26 years if natural gas), indicating an average of 4-5 years difference if derived from coal and 2-3 years difference if derived from natural gas.

Only in the scenario with historical lower rates of technological advancement and coal as the incumbent source of electricity will the tax have a more significant impact of accelerating adoption by an average of 8 years – however projections still indicate that widespread adoption will occur on average in almost 34 years in this scenario.

PELEC +2.89%	COAL			NATURAL GAS		
CO2 Tax (\$65/ton CO2)						
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	10y 1m	9y 10m	9y 7m	11y 6m	11y 5m	10y 7m
40%	18y 10m	17y 10m	14y 11m	20y 4m	19y 1m	15y 10m
50%	21y 4m	20y 6m	16y 6m	23y 2m	21y 4m	17y 10m
60%	25y 1m	23y 5m	18y 5m	28y 0m	25y 0m	19y 10m
70%	30y 5m	27y 4m	20y 7m	32y 10m	29y 3m	22y 5m
80%	36y 11m	32y 2m	23y 4m	42y 6m	33y 10m	26y 2m
90%	Not within 50 years	46y 4m	28y 7m	Not within 50 years	45y 9m	32y 5m

Table 2.10 – Impact of \$65/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = +2.89%, r=3%)

Results indicate that the impact of a \$65/ton CO2 tax would be modestly higher than in the scenario with consumer incentives or the \$21/ton CO2 tax – accelerating adoption by 2-4 years if the incumbent electricity source were derived from natural gas, and 4-8 years if derived from coal. Consistent with previous results, the impact is diminished in the case of the higher rate of technological change.

Concurrently, a carbon tax of \$65/ton CO2 would raise the price of a gallon of gasoline by \$0.58, and a barrel of crude oil by \$27.95.

Carbon Taxes At \$150/ton CO2: While a carbon tax of \$150/ton CO2 has not been included in government estimates of the social cost of carbon (SCC), it has been suggested as representing considerations of catastrophic climate outcomes more accurately than lower estimates (Pindyck 2013).

The results for the impact of a carbon tax of 150/ton CO2 are shown in table 2.11. If the recent rates of cost decline are maintained, the carbon tax would result in a widespread shift within 18.5 - 20.5 years, albeit this representing a moderate acceleration of an average of 6-8 years above baseline results free of any incentives.

PELEC +2.89%	COAL			NATURAL GAS		
(\$150/ton CO2)						
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	6y 9m	6y 10m	7y 3m	8y 10m	8y 9m	8y 11m
40%	13y 11m	13y 0m	11y 10m	17y 4m	16y 1m	14y 1m
50%	16y 3m	15y 2m	13y 5m	19y 11m	18y 5m	15y 9m
60%	19y 2m	17y 9m	15y 5m	23y 4m	20y 10m	17y 5m
70%	22y 11m	21y 3m	17y 5m	27y 11m	24y 1m	19y 4m
80%	29y 3m	26y 5m	20y 3m	33y 7m	29y 3m	22y 4m
90%	46y 7m	36y 11m	25y 3m	Not within 50 years	39y 6m	26y 7m

Table 2.11 – Impact of \$150/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = +2.89%, r=3%)

The impact will be more significant in the scenario with historical lower rates of technological advancement – accelerating adoption by an average of 10.5 and 15.5 years, given the incumbent source of electricity is derived from natural gas and coal respectively. However projections still indicate a widespread shift within an average of 31 and 26 years respectively.

Projections indicate that a tax of \$150/ton CO2 applied to the lower technical change scenario will replicate the baseline results for the higher rates of technical change free of any incentives, if the incumbent source of electricity is derived from coal. However, it will <u>not</u> replicate baseline results for electricity derived from natural gas – a higher carbon tax than \$150/ton CO2 would be necessary to do so.

Concurrently, a \$150 carbon tax would raise the price of a gallon of gasoline by \$1.33, and the price of a barrel of crude by approx. \$65. In addition, a \$150 tax would more than

double the current price of electricity (if derived from coal), rendering it almost as high as the current cost of solar free of incentives.

2.5 Conclusion

This paper considers the question of how to transition to a meaningful percentage of solar energy in a sustainable way and which policies are most effective in accelerating adoption. We develop a stochastic dynamic real options model evaluating the threshold and timing of the consumer's optimal investment decision given two sources of uncertainty, and obtain a cumulative likelihood and timing of substitution amongst energy resources and towards solar under plausible rates of technological change, subsidies and carbon taxes.

Based on our specification, results indicate that there will be a widespread shift towards solar PV in the residential and commercial sector in under 30 years – and that this can occur independent of downstream incentives and carbon pricing policies (at \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2). In general, results across all scenarios consistently indicate that average historic consumer subsidies and carbon pricing policies have a modest effect in accelerating adoption, and may not be an effective part of climate policy in this regard.

The results demonstrate that R&D support and further technological change is the crucial determinant in accelerating widespread adoption of solar PV - suggesting that subsidies and taxes don't make a substantial difference in a technology that's not viable, while research does. This further suggests that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant of widespread transition to solar and plausibly other backstop technologies – and that it should play a key role in policy measures intended to combat climate change.

The results do not imply that carbon pricing shouldn't play a role in climate policy in general. Carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies – however it has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2. Suggesting, that if a widespread transition to solar energy is likely to happen in this sector, it will be because of R&D and technological advancement.

There are several limitations of this study that should be addressed in further research. One, that we are assuming that R&D and technological change are independent of adoption. In reality, the innovation process is a continuum, such that the R&D and manufacturing processes are integrated and exhibit learning by doing effects. Inasmuch, taxes and subsidies may provide an incentive for adoption that enhances learning - which has not been included in this study. Despite the analysis by Nemet (2006) suggesting that learning by doing only weakly explains changes in the most important factors influencing cost reductions in solar PV over the past 30 years, the current omission of such effects should be addressed in future research. Another limitation is that this study cannot capture the effect of subsidies that reduce the initial cost, but which tend to expire - which would aim to counter the Dixit Pindyck effect and would affect the results.

Further, the implications of a widespread shift towards solar in this sector should be examined in further detail in terms of GHG emissions and climate change outcomes. We have seemingly assumed the shift towards solar in this sector as desirable, however this should ultimately be evaluated against the prospects and impact of other technologies - including solar adoption in the utility sector.

Additionally, the estimated probability of adoption at each moment which we were able to derive as a function of each policy provides a key tool to assess the expected rate of return of various policies, which should be evaluated in future research. Nevertheless, the results of this study remain robust across varying levels of interest rate, technological change and incentives - with significant policy implications about the relationship between research subsidies and consumer subsidies in accelerating the widespread adoption of solar PV.

The results consistently indicate that average historic consumer subsidies and carbon taxes will have a decidedly modest impact in encouraging the adoption of a technology that is not viable. Instead, continued R&D support and technological advancement is the crucial determinant and main driver of adoption, outweighing the effect of subsidies and taxes - and it should play a key role in climate policy.

Chapter 3

The Transition to Renewable Energy Technologies: Optimal Policies Over Time*

3.1 Introduction

Climate change is fundamentally an energy issue, and the transition towards clean technologies will play a key role in our efforts to meet deeper, long term green house gas (GHG) reductions²³, beyond energy efficiency (EE) and carbon capture and storage (CCS). Meeting these goals will require a "significant reorientation of national energy trajectories" (Sagar et al., 2006) and the development and deployment of renewable technologies that are not yet commercialized (Williams et al., 2012; Chakravorty et al., 1997; Margolis and Kammen, 1999; Goulder and Parry, 2008).

Achieving this transition and the necessary technological breakthroughs will depend on both technical as well as economic forces (Sunding and Zilberman, 2001), and the government's role will remain crucial given the public goods aspect of energy and environmental services. Technology and technology policies are pivotal, and policy incentives will play an important role in enabling the transition towards renewable energy technologies, including government investment in energy research and development (R&D) programs as well as early deployment of nascent technologies.

The central issue in this regard remains how best to enable technological change, and accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system. This raises the question of how best to assess the tradeoffs between alternate policy measures and crucially, how much and when to invest in which policy measure.

^{*} Co-authored with Gordon Rausser and David Zilberman. The authors gratefully acknowledge financial support from the Energy Biosciences Institute at the University of California, Berkeley.

 $^{^{23}}$ Several US states have recently announced the goal of reducing greenhouse gas emissions by 80 percent below their 1990 levels by 2050. The magnitude of carbon cuts required is large – beyond what EE and CCS measures can achieve (Williams et al., 2012).

The key question remains - how we are allocating our public resources, and whether we should allocate public expenditure in one direction or the other, and under which circumstances? I.e. what is the optimal allocation between differing policy measures, including the balance between R&D investments and downstream policy instruments across emerging renewable energy technologies?

The current allocation of US public expenditure on R&D subsidies versus deployment subsidies²⁴ for solar PV technologies indicates that US public R&D expenditure has averaged at approximately \$115 million per year from the mid 1980's to 2008²⁵. This amount dwarfs in contrast to public spending on deployment and commercialization subsidies. In 2007, CA alone committed to spending \$3.3 billion over 10 years on upfront consumer incentives for solar installations as part of the CSI, NSHP and POU programs²⁶ - by far surpassing the \$115 average annual federal budget for Solar PV R&D. And yet, despite the substantial resources devoted to consumer adoption, in 2012 Solar amounted to little over 1% of generated electricity in the US (EIA Electric Power Monthly, March 2013), and technically contributed the smallest share amongst all renewable-generated electricity.

IEA estimates of worldwide energy subsidies (IEA, 2011; IEA, 2012) reveals that in 2010 alone, fossil-fuel consumption subsidies amounted to \$409 billion, and subsidies given to renewable energy amounted to \$66 billion (which was a 10% increase over 2009). Of this, \$44 billion went to renewable based electricity (i.e. electricity generation from biomass, wind, solar PV in buildings, and geothermal energy) and \$22 billion went to biofuels.

Renewable energy subsidies in 2010 were the highest in the EU at \$35 billion, followed by the US at approximately \$18 billion. Together both the EU and the US accounted for almost 80% of the worldwide total in renewable energy subsidies at approximately \$52 billion in one year alone. Notably, Solar PV received 28% of total renewable electricity subsidies in 2010 globally (i.e. approx \$18 billion worldwide), despite accounting for only 4% of subsidized renewable electricity generation.

IEA estimates for 2011 showed a 24% increase over renewable energy subsidies from 2010, with a total of \$88 billion spent worldwide. Of this, \$64 billion went to electricity,

²⁴ Goulder and Parry (2008) define technology policies as consisting of technology development (R&D) and technology deployment, in the sense that once technologies have been developed and are ready for commercialization, their deployment could be pushed by additional policy interventions which may be warranted on efficiency grounds if there are additional market failures that impede the diffusion process - and requiring public sector responses to encourage early adoption of new technologies through targeted policy incentives such as subsidies to favorable technologies, technology based and performance based standards, mandates, and government procurement programs. ²⁵ Notwithstanding the recent increase in total R&D funding in 2009, 2010, and 2011 due to the 2009

²⁵ Notwithstanding the recent increase in total R&D funding in 2009, 2010, and 2011 due to the 2009 Recovery Act.

²⁶ With a concurrent commitment of a total of \$50 million on R&D investments over 10 years under the same CA initiative.

and the remainder to biofuels. Globally, Solar PV received more than any other renewable energy technology for electricity generation (\$25 billion), followed by wind (\$21 billion) and bioenergy (\$15 billion). Consistent with 2010 patterns, the EU and the US accounted for almost 80% of worldwide renewable energy subsidies in 2011. The EU once again provided the highest level of support in the world at almost \$50 billion in one year alone, followed by the US at \$21 billion.

In general, current subsidies to solar PV far surpass R&D investments, yet solar PV accounted for only 4% of subsidized renewable electricity generation globally in 2010, and little over 1% of generated electricity in the US in 2012. This raises the critical question of how we are allocating our scarce public resources, and whether this current split between R&D and deployment policies is optimal. I.e. how do we assess the tradeoffs between alternate policy measures, what is the optimal allocation of public resources, and crucially, when should we invest in which policy incentive across emerging renewable energy technologies?

This paper contends that optimal policies will change over time, and that the technology under consideration will largely determine how and when to allocate available funds. And that the relative emphasis on various policy measures should depend in part on the characteristics of the technology – i.e. that technology features should guide and inform energy policy design in order to be effective. This implies that optimal design may require differing polices for differing technologies, based on the characteristics of the technology features in policy and its stage of development. In this paper, we emphasize technology features in policy design, and contend that this will crucially affect the appropriate timing and sequencing of policies, as well the impact and effectiveness of differing policy measures.

Policy design and the appropriate timing and sequencing of policies, without consideration of the characteristics of the technology and its stage of development are incomplete. We find that targeted policy should consider every stage of the technology innovation cycle - from R&D to commercialization in overcoming barriers to the development and widespread adoption of nascent technologies.

This paper illustrates the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards renewable energy technologies. We stress that optimal policies will change over time, driven primarily by the characteristics of the technology, and its stage in the innovation cycle – and that *this* will crucially determine the impact, gains and tradeoffs between alternate policy measures such as R&D policies, deployment policies, and carbon pricing policies.

Based on our analysis and results we find that there is a pressing need for the reallocation of public resources from consumer subsidies towards public R&D budgets in emerging energy technologies such as solar PV, and plausibly other backstop technologies. We argue for an expanded role of aggressive R&D policies and increased public R&D funding – and contend that there is an imbalance in resources allocated towards adoption and commercialization subsidies relative to R&D investments for a technology such as solar PV that is not commercially viable. Our results indicate that there is a pressing need

for increased R&D funding relative to consumer subsidies for emerging technologies such as solar PV which are not commercially viable – and that this should be the key policy objective in ensuring that emerging energy technologies and systems are commercially ready.

Despite the inherent uncertainty of R&D investments and outcomes, given the significant innovation required in the energy sector with respect to climate change and the development of clean energy technologies - it is unlikely for any major technical breakthroughs to occur without R&D. We contend that increased and aggressive R&D investments will be the key policy initiative in enabling the transition towards clean energy technologies such as solar PV in a sustainable manner - and that the current emphasis on consumer subsidies with relatively low investments in R&D is not optimal for a technology such as solar PV (Torani, Rausser, and Zilberman, 2014).

Admittedly, deployment policies and learning-by-doing (LBD) are a crucial part of technical change. And they are theoretically justified to the extent that capacity driven experience can lead to improvements such as greater expertise and cost reductions in technologies²⁷ – often playing a key role in the large-scale uptake of new energy technologies. However, in general, learning is not an automatic byproduct of cumulative installed capacity, and should not be taken as such. While learning rates have been observed to play a vital role in a wide range of industries, including energy technologies, the potential for LBD may fundamentally differ among technologies, and at different stages of a technology. E.g. Nemet (2006) suggests that LBD only weakly explains changes in the most important factors influencing observed cost reductions in solar PV over the past 30 years. In general, we do not yet have a clear understanding of what leads to experience and learning gains – despite numerous efforts to disentangle and understand the mechanism behind LBD and its cost reducing potential (Argote and Epple, 1990; IEA, 2000). Deployment policies are justified if a LBD potential exists, however it is crucial to evaluate and determine this potential and concomitant gains while committing \$88 billion on renewable energy subsidies in one year alone²⁸.

Even when deployment policies are justified, the appropriate timing and sequencing in the technology development stage is crucial. We contend that technology and policies must be deployed in a coordinated manner to be effective and achieve emissions reductions benefits at an acceptable cost. Investments in commercialization and deployment subsidies before sufficient R&D investments and breakthroughs have occurred will be ineffective and unsustainable, or alternatively will need to be very high to have any significant impact (Torani, Rausser, and Zilberman, 2014). Widespread adoption and commercialization of emerging and unproven technologies and systems will be unlikely to occur unless sufficient major technological discoveries and improvements have taken place - which will need to be driven by appropriate and sufficient R&D investments. Even if deployment policies are justified during the pre-commercial phase (and not intended for mature technologies) – the appropriate timing and sequencing of

²⁷ With feedback into the R&D process and technology refinement.

²⁸ IEA estimates of renewable energy subsidies spent globally in 2011.

policies is still crucial. It makes little economic sense to invest billions of dollars in deployment subsidies and LBD prematurely, when dealing with a technology that is not sufficiently viable and before sufficient technological discoveries have been made (and with relatively few resources allocated towards R&D and technological discoveries). The logical sequence of policies necessitates first making sufficient investments and allocating resources towards R&D and the necessary technological discoveries, which can then be followed by downstream policies to enhance adoption, experience and LBD which may also feed back into the R&D process for further technological improvement and refinement (provided a LBD potential exists). Deployment policies and LBD before the technology is sufficiently viable, and to the extent that is currently being allocated. may be premature and will subsequently need to be extremely high to be effective. We contend that the appropriate timing and sequencing of policies in parallel with the characteristics of the technology under consideration is paramount, and that the first and foremost, R&D investments are required which can then be followed by deployment and commercialization subsidies where appropriate. However, we contend that deployment subsidies e.g. in the form of consumer subsidies must also be short lived and provided for a limited amount of time in order to be effective and counter the Dixit and Pindyck delay effect, i.e. given rational expectations, people will delay investment and adoption of a nascent technology due to the expectation of further technological change and future cost reductions (Torani, Rausser, and Zilberman, 2014).

Balancing R&D and deployment investments is a pertinent issue, with a concrete tradeoff between allocating funds in one direction of the other. We contend that optimal allocation of public resources may require a different split between R&D and deployment for different technologies, based on the characteristics of the technology, its stage of development, and the gains achievable through R&D and deployment efforts. The appropriate emphasis and sequencing of R&D and learning investments is a pertinent issue, and optimal timing and allocation between the two depends in part on the characteristics of the technology itself and the appropriate sequencing of R&D and learning investments which will greatly affect the impact and effectiveness of differing policy incentives.

It is in this context that we also examine the effectiveness of an emissions control policy such as a carbon tax in encouraging technology adoption at the early stages of an emerging renewable energy technology, while the technology is not commercially viable. While almost all economic studies find a case for imposing immediate restraints on GHG emissions, with many researchers advocating for an immediate, and at least initially low carbon tax (even if the true SCC is unknown), we contend that reasonable and plausible levels of CO2 taxes may not be effective in encouraging technology adoption and reducing emissions while clean technologies are not commercially viable as yet.

Carbon pricing has been suggested as a policy to reduce emissions by both impacting demand and encouraging the adoption of new technologies – and some suggest even as a policy to induce technological innovation. Most argue for small CO2 tax (at least at first) even if the true SCC is unknown. However, to be effective in encouraging technology adoption at an early stage of technological innovation, we contend that a large CO2 tax

may be needed, far larger than suggested at reasonable levels – with significant implications on distributional effects and political feasibility. We contend that if clean technologies are not commercially viable, it will impact the effectiveness of a realistic and plausible CO2 tax, and raise the question of alternate policy measures that may be more effective in accelerating the transition to sustainable energy systems given our current technology landscape (Chu and Majumdar, 2012).

Given relatively low price elasticities of demand and uncertainty regarding the effectiveness of carbon pricing in inducing technological change, the effect of carbon pricing on adoption of emerging clean technologies is extremely relevant. Given the high cost of emerging renewable energy technologies, we contend that reasonable levels of CO2 tax will have a modest effect in encouraging technology adoption, and that CO2 taxes may have to be very high to be effective in encouraging the adoption of emerging clean technologies during the early stages of technological innovation.

We contend that the stage of technological innovation will determine how effective policies such as reasonably priced consumer subsidies or carbon taxes will be in encouraging clean technology adoption and reducing emissions. We highlight the fact that reasonable levels of consumer subsidies and carbon pricing policies will have a decidedly modest impact in encouraging technology adoption when technologies are in their nascent stages and not viable as yet. E.g. Torani, Rausser, and Zilberman (2014) find that reasonably priced carbon taxes at \$21/ton CO2 or \$65/ton CO2 will have only a modest impact on current Solar PV adoption levels. Instead, their results demonstrate that further technological change is the crucial determinant and main driver of adoption of solar PV, outweighing the effect of subsidies and taxes at levels up to \$150/ton CO2. The results demonstrate that R&D support and further technological change is the crucial determinant in accelerating widespread adoption of solar PV - suggesting that subsidies and taxes don't make a substantial difference in a technology that's not commercially viable, while research does.

Their results further support the notion that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant of a widespread transition to solar and plausibly other backstop technologies – and that downstream incentives or carbon pricing policies will have to be very high to be effective at this stage of the technology (i.e. higher than \$150/ton CO2). In general, they state that carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies and may play a role in climate policy - – however it has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2. Suggesting that if a widespread transition to solar energy is likely to happen, it will be because of further R&D and technological advancement – and that R&D and technological innovation should play an increased role in climate policy. We contend that the stage of technological innovation and subsequent technology readiness will determine how effective a reasonably priced carbon tax will be in encouraging clean technology adoption and emissions. With many clean technologies currently not commercially viable, a reasonably priced carbon tax may not have much of

an impact on technology adoption and may not be an effective policy for reducing carbon emissions.

Once again we emphasize that technology and policies must be deployed in a coordinated manner such that the emission reduction benefits are achieved at an acceptable cost (Williams et al., 2012). Our results suggest that the first and most important stage does not lie in imposing CO2 taxes, but rather in investing in R&D and technological advancements. Once clean technologies are sufficiently ready, reasonably priced carbon taxes will bite to a larger extent and be more effective at plausible levels. Reasonable carbon pricing when technologies are not sufficiently developed will not be effective in encouraging clean technology adoption as consumers and producers will not be able to switch to clean technologies if the cost of the technology is prohibitive. In effect, technologies need to be sufficiently developed to make this transition economically sustainable, as the switch to clean technologies will not be likely if they are unviable and relatively costly. Thus despite calls for immediate imposition of carbon taxes (at least at initially low levels) we contend that one plausible strategy would be either to introduce high CO2 taxes or to subsidize R&D first, followed by deployment and LBD, and then to impose reasonable carbon taxes - in which case scientific advances and technological changes would make CO2 emissions abatement less costly, and CO2 pricing would be effective at reasonable levels.

Crucially, this points towards the fundamental issue that R&D is a pressing and necessary part of technological innovation and our energy transition, particularly in the early stages of emerging technologies. While deployment and LBD further comprise an important part of technological change, balancing R&D and deployment investments, and the optimal timing and allocation between the two depends on the characteristics of the technology itself. Carbon pricing is justified, however the central question in this regard remains how much and how fast to react to the threat of global warming, and at what levels carbon pricing will be effective (Nordhaus, 2007). In general, we contend that an emphasis on technology features in policy design is crucial, since it will affect the impact and effectiveness of policy measures and will be critical in the transition towards more sustainable energy systems.

We illustrate the broader issue that that policy design independent of the stage and characteristics of the technology under consideration is incomplete. The technology under consideration should in part guide and inform energy policy, as it will affect the impact and effectiveness of differing policy measures, and will determine the logical sequence and timing of policies. However we find that these considerations are noticeably absent from most studies evaluating and comparing differing policy mechanisms - most of which focus solely on considerations of cost effectiveness, performance under uncertainty, distributional impacts etc. when assessing tradeoffs between policy instruments. We contend that what is notably absent in most discussions evaluating policy instruments is a consideration of the characteristic of the technologies in question - including the stage of technology innovation, and the optimal timing and sequencing of policies in this regard. And these factors will undoubtedly affect the impact

of the differing policy instruments and are a crucial determinant of the effectiveness of policy instruments.

In this paper, we examine the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in LBD and deployment polices, and in CO2 taxes. This paper is organized as follows. Section 3.2 discusses the different stages of the innovation process and the main drivers of technological change which will play a significant role in guiding energy policy and affect efficiency of such. Section 3.3 outlines the significance and challenges of R&D policies, and highlights funding trends and the impact of such. Section 3.4 examines the timing and effectiveness of carbon pricing policies, and section 3.5 discusses the significance of LBD and deployment policies. Lastly, section 3.6 concludes with a discussion of the main results and suggestions for future research.

3.2 The Innovation Process and the Drivers of Technological Change

Technological innovation and the development of new energy technologies remains fundamental in the transition towards a clean and efficient energy economy. This paper contends that the characteristics of the technology under consideration (and its stage in the innovation cycle) will in part determine how and when to allocate available funds, influence policy effectiveness, and should in large part guide and inform energy policy.

Policy design and the appropriate timing and sequencing of policies, without consideration of the characteristics of the technology and the stage it is in, is incomplete. In particular, targeted policy must consider every stage of the technology innovation cycle – from R&D to commercialization in overcoming barriers to the development and widespread adoption of nascent technologies. We discuss the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards (and widespread adoption of) renewable energy technologies. It is in this context that we examine the different stages of the innovation process and the main drivers of technological change which will play a significant role in guiding energy policy and affect the efficiency of such.

Broadly speaking, the process of technology innovation consists of the R&D phase, demonstration phase, deployment, diffusion and commercial maturity, followed by the ultimate decline phase. However, it is important to note that innovation is not a linear process, exhibiting various interdependencies, overlap, and feedback loops between stages - most notably the R&D and early deployment stages. In addition, often the stages themselves cannot be clearly disaggregated, distinguished or compartmentalized (Sagar et al., 2006).

The initial stage of the technology life cycle is the innovation or R&D stage, followed by the post research and early phases of demonstration and deployment of the nascent technology. The diffusion stage represents the market penetration of the new technology,

ultimately followed by the maturation stages of saturation and then senescence, which is signified by a decline in the use and eventual substitution by another technology (Grubler, 1998; Grubler et al., 1999).

Of the different stages of the technology life cycle, the two main contributors of technical change are captured in the complementary and inter-linked stages of R&D and learning by doing (LBD) (Carraro et al., 2003), and both stages are vital to the process of technical change.

Despite the inherent uncertainty of R&D outcomes, it is unlikely for any major technical change to occur without research and development. However, while R&D occurs largely during the early stages of technical development, even successful R&D outcomes rely crucially on the capacity to learn through deployment in order to surmount the initial higher costs and other barriers (e.g. infrastructure or institutional barriers) that may prevent further widespread commercial deployment of the new technology. In other words, the commercialization of research outcomes critically depends on LBD and the productivity growth and cost reduction acquired through deployment and experience, without which R&D outcomes may never be followed by widespread commercialization of the technology (Sagar et al., 2006).

In general, the process of innovation, upgrading, and commercialization is a continuum, with R&D and manufacturing processes being integrated and exhibiting LBD effects (Arrow, 1962; Clemhout and Wan, 1970; Feder, 1976; Sunding and Zilberman, 2001). Undoubtedly, LBD remains a crucial element of early deployment – referring to experience driven cost reductions as a function of cumulative production, installed capacity or deployment, and is often represented by learning or experience curves (IEA, 2000). In theory, LBD can lead to cost reductions, greater expertise in technology operation, or institutional transformations necessary to support the introduction, diffusion and widespread use of new technologies (Sagar et al., 2006), with these improvements often playing a key role in the large-scale uptake of new energy technologies (van der Zwaan and Seebregts, 2004).

It is crucial to note that while learning rates have been observed to play a vital role in a wide range of industries, including energy technologies (van der Zwaan and Seebregts, 2004; McDonald and Schrattenholzer, 2001), the potential for LBD may fundamentally differ among companies, technologies, and even at different stages of a technology. In general, learning rates are most frequently observed, and are highest during the initial stages of technology deployment - exhibiting gains that are increasingly difficult to sustain as the technology matures. Predictably, the gains from learning may diminish as a technology matures and as future development is unable to sustain past progress ratios and cost reduction factors.

Additionally, the potential for LBD and learning rates may differ amongst technologies (McDonald and Schrattenholzer, 2001). For example, Nemet (2006) suggests that LBD only weakly explains changes in the most important factors influencing observed cost reductions in solar PV over the past 30 years. Whereas Khanna and Chen (2014) examine

competing hypothesis explaining the decline in processing costs of US corn ethanol since 1983, and conclude that LBD played an important role in reducing corn ethanol processing costs, exhibiting a learning rate of 0.25.

In general, while numerous efforts have been made to disentangle and understand the details and mechanism behind LBD and the cost reducing potential (Argote and Epple, 1990; IEA, 2000) – we still lack a clear understanding of the exact mechanism and conditions under which deployment leads to learning, and how to maximize and replicate this potential both within and across industries. In general, we have yet to obtain a clear understanding of the relative contribution of the differing mechanisms which lead to learning²⁹ and cost reductions which remain essential for developing policies to promote the transition to sustainable energy technologies (Sagar et al., 2006).

It should also be noted, that not all deployment and experience may lead to learning gains and cost reductions. Aside from the fact that the process itself is poorly understood, it is problematic that by definition, learning curve estimates have been based on technologies that have survived, representing a biased sample (Sagar et al., 2006). Technologies that have not survived beyond an early stage of development or deployment (Grubler, 1998) are omitted from the learning curve methodology. Hence one should employ caution when employing learning curves in estimating possible competitiveness of emerging energy technologies.

In general, while the significance of LBD as a key element of deployment is not disputed, the learning process, learning potential and mechanism still remain poorly understood. Additionally, feedback from deployment and learning can also feedback into the technology R&D process, leading to refinement and improvement in technologies and future development. However, this requires both coordination and linkages between the R&D and the deployment processes. In general, it remains important to deconstruct both the R&D and LBD processes, and to improve the design of early deployment efforts and find conditions under which technologies can be most productively deployed with the greatest learning gains. This will invariably affect the impact and efficacy of policy measures and the optimal timing of policy instruments.

3.3 R&D and Innovation Subsidies

Undoubtedly, investments in R&D will play a crucial role in responding to the challenges posed by climate change - with significant innovation required in the energy sector in respect to developing clean energy technologies. R&D subsidies are unquestionably important and will play a key role, despite the inherent uncertainty of R&D outcomes. And despite the fact that no straightforward relationship exists between the amount of public R&D investments made, and potential outcomes in terms of improvement in energy systems (e.g. carbon factors or energy intensities). Fact remains that it is unlikely

²⁹ E.g. learning-by-manufacturing, learning-by-operating, learning-by-implementing etc.

for any major technical change to occur without research and development – as technological breakthroughs have historically not been achieved without R&D investments.

In light of the challenges of climate change and the required transition to clean and efficient energy systems, there is a pressing need for public R&D budgets to be maintained or increased, since R&D is an unquestionable and necessary part of this transition (Margolis and Kammen, 1999; Sagar et al., 2006; Torani, Rausser and Zilberman, 2014). Given the public goods aspect of such a transition and the existence of environmental externalities and under- or un-priced environmental goods (i.e. low carbon technologies), as well as the private sector's under-investment in basic research, and its desire to prevent the downside risk from renewable energy investments, the government's role will remain crucial in achieving significant advances in new energy technologies (Rausser and Papineau, 2008; PCAST, 1997).

Despite the inherent risk and uncertainty in R&D investments and outcomes, studies examining the impact of R&D investments and energy innovation have suggested that past federal spending on energy R&D has often yielded considerable net benefits and has led to the development of innovative technologies and a significant impact on the energy sector (NRC, 2001).

Conversely, studies based on high levels of correlation between US R&D spending and patents issued in the energy sector have also determined that cutbacks in energy related R&D had a significant negative impact on innovation in the energy sector. Margolis and Kammen (1999) contend that R&D funding and innovation in new energy technologies is closely linked, and that there is a disconcerting underinvestment in energy technology R&D relative to other technology intensive sectors of the economy. In their study, they examine the total US investment in energy related R&D (both public and private) from 1976-1996 which increased from approximately \$100 to \$200 billion, and the increase in the number of US energy related patents issued which increased from 70000 to 110000 – indicating the proportional increase of patents with R&D investments during this period as empirical support of a significant link and high degree of correlation between the two.

They further point towards a boom & bust cycle in which R&D cutbacks during the 1980s and 1990s (reaching a low of \$4.3 billion in 1996) were accompanied with a parallel decline in patents related to energy technologies from a high of 228 in 1981 to a decline and eventual low of 54 in 1994. Indicating again that the cutbacks in energy related R&D had a significant impact of innovation in the energy sector. Another finding of their study points towards the striking divergence between the low R&D intensity in the energy sector as compared to R&D intensities in other sectors (e.g. drugs and medicine, industrial chemicals and scientific and communications equipment), thereby raising the concern about the relatively low level of investment in energy technology R&D.

In general, trends in public-sector energy technology R&D funding have shown a significant decline over the past two decades across the industrialized world, and remains

a cause for concern since this decline is invariably likely to impact the energy sector's capacity to innovate, and to respond to the challenge of global climate change.

Surveys of energy R&D funding levels in IEA member countries, display that public energy R&D budgets have been declining significantly in real terms since the early 1980s: public energy R&D budgets show an overall decline of 39% between 1980 and 1995, with particularly sharp declines in Germany, the UK and the US. Of this decline, nuclear funding fell by 40%, fossil fuel funding fell by 58% and funding for renewable energy fell by 56%. However, investments also displayed a diversity in trends, with some countries reducing their energy technology R&D budgets across all technologies, while other countries refocused their technology portfolios to eliminate some and favor other technologies (Margolis and Kammen, 1999).³⁰

In the US, public sector renewable energy R&D funding (versus energy R&D funding in general) has increased only modestly over the years. During the years 1978-2002, on average renewable energy funding comprised 11% of the total energy R&D budget (which also included energy efficiency, fossil fuels, nuclear, and hydrogen and fuel cells R&D) while the period 2003-2011 on average renewable energy funding comprised 13.5% of the total R&D budget³¹ (figure 3.1). The breakdown of renewable energy R&D funding has steadily decreased over the years, while biofuels' funding has steadily increased – with both these technologies currently comprising the two largest shares of US public renewable energy technology funding (figure 3.2). Solar has previously and traditionally commanded the largest share of renewable energy R&D funding - averaging at approximately \$115million per year from the mid 1980's to 2008. In addition, the share of wind energy R&D funding has seen a gradual but steady declined over the past decades.

³⁰ For example, nuclear technology R&D was cut back in the UK, US, Germany and Italy while it was increased in Japan and France.

³¹ Notwithstanding the recent increase in total R&D funding in 2009,2010, and 2011 due to the 2009 Recovery Act



Fig. 3.1: Total Energy RD&D in Million USD (\$2012), by FY Source: IEA R&D Database 1974 – 2011



Fig. 3.2: Share of Renewable Energy R&D Funding (%) by Technology, 1974-2011 Source: IEA R&D Database 1974 – 2011

Notwithstanding arguments for increased government energy R&D, historic trends however don't reveal a clear correlation between R&D investment and improvement of the energy system and relevant indicators such as energy and carbon efficiencies (e.g. energy intensity (EI)³² or carbon factor (CF)³³). For example, Sagar et al. (2006) examine past trends amongst selected industrialized countries over the time period 1975-1999 which show no clear relationship between the average annual changes in EI, CF and public R&D budgets and intensity³⁴, even when accounting for potential time lags between R&D spending and changes in the energy sector, and accounting for the fact that some R&D programs could affect one indicator but not the other.

Instead, results indicate that many countries with the highest R&D intensities displayed relatively lower rates of EI improvements. Even accounting for the fact that it is harder for more efficient countries to achieve reductions in EI and CF, the results showed that other countries with relatively lower levels of public R&D funding have been more successful at achieving improvements in their energy and carbon efficiencies (e.g. Netherlands and Canada).

In general, Sagar et al. (2006) point to the fact that no straightforward relationship exists between the level of R&D investment and the improvement of the energy system – and provides potential explanations for this, none of which are an argument against increased R&D budgets.

Undisputedly, the factors ultimately influencing a countries energy sector and EI, CF indicators include energy supply sources, and structural factors (e.g. a shift from manufacturing to services). In particular, the limited impact of energy R&D spending and indicators could be explained by the specific focus of energy R&D expenditures (e.g. as in the case of Japan where over 75% of Japanese government spending is on nuclear power, which accounts for less than 15% of the country's energy supply), or crucially, weak linkages between R&D efforts and the ultimate deployment of technologies, or lastly that public R&D has often not been targeted enough to specifically reduce EI or CF of economies. In all, pointing to the fact that the lack of correlation between public R&D budgets and EI and CF factors may actually be an indication of the issue with using R&D spending levels as a measure of these capabilities.

Clearly, while public R&D budgets alone are not enough to transform a country's energy sector, (since they alone do not automatically lead to a certain level of technological change in the real world), they have indisputably been the basis for innovation and technological advances. And without maintaining or increasing R&D budgets, addressing climate change and the transition to a sustainable energy system will be even more challenging.

³² EI, the level of energy consumption per unit of GDP

³³ CF, the amount of carbon emissions per unit of energy consumption

³⁴ Public R&D expenditures per unit of GDP

In addition, Goulder and Parry (2008) justify public R&D and innovation policies on the grounds that: (i) Emissions control policies may be incapable of bringing about technological breakthroughs since they provide invention incentives only indirectly by emissions pricing or by raising the costs of conventional "dirty" production methods through direct regulation. (ii) They address market failures beyond the pollution externality, e.g. the inability of inventors or innovators to fully appropriate the returns from the knowledge they create. Thereby implying that incentives for clean technology R&D will be inefficiently low, even if pollution externalities are appropriately priced. They argue that no single instrument can effectively correct market failures from both emissions reduction through one instrument alone involves considerably higher costs than employing two instruments and is an inefficient way to promote innovation (Fischer and Newell, 2008; Schneider and Goulder, 1997).

Undisputedly, R&D is in itself not a sufficient, but a necessary part of technology innovation & transition. Deployment and LBD remain a crucial part of technological change, as well as the ability to determine at what stage to employ which policy mechanism, which will greatly affect the impact and effectiveness of differing policy incentives (Torani, Rausser, Zilberman, 2014).

Admittedly, a focus only on R&D and the development of new technologies without emphasizing the role of deployment efforts and LBD is incomplete – however balancing R&D and deployment investments, and optimal timing and allocation between the two depends in part on the characteristics of the technology itself. This is a pertinent issue in policy analysis, and it depends on the kind of technology, the stage it is in, and the appropriate sequencing of R&D and learning investments (Torani, Rausser, Zilberman, 2014). Different technologies may require a different split between R&D versus deployment investments, based on the characteristics of the technology and the gains achievable through R&D and deployment efforts.

For example, Torani, Rausser and Zilberman (2014) find that average historic consumer subsidies and carbon pricing policies (up to \$150/ton CO2) have a modest impact in accelerating adoption of Solar PV in the residential and commercial sector across plausible rates of technological change - making virtually no difference in certain cases, hence not being an effective part of climate policy in this regard. Their results demonstrate that further technological change alone is the crucial determinant and main driver of adoption of Solar PV, outweighing the effect of subsidies and taxes. Suggesting that subsidies and taxes don't make a substantial difference in a technology that's not viable – instead that research does. Their results show that R&D support and technological advancement in solar PV is the crucial determinant in accelerating widespread adoption of solar PV and should play a key role in climate policy³⁵.

³⁵ Their results are robust across varying levels of electricity prices, interest rates, technological change, and incentives.

Their results further support the notion that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant of a widespread transition to solar and plausibly other backstop technologies – and that downstream incentives or carbon pricing policies will have to be very high to be effective at this stage of the technology (i.e. higher than \$150/ton CO2). However, they state that carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies, and may thus play a role in climate policy – however that carbon pricing has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2. Suggesting that if a widespread transition to solar energy is likely to happen in this sector, it will be because of further R&D and technological advancement.

Similarly, Sagar et al. (2006) state that e.g. while fuel cells are advanced enough that they should be subject to both types of investment, a technology like fusion energy (with an operable commercial prototype likely half a century away) still requires only R&D investments.

Crucially, this points towards the fundamental issue that R&D is a pressing and necessary part of technological innovation and our energy transition, particularly in the early stages of technological innovation. While deployment and LBD further comprise an important part of technological change, balancing R&D and deployment investments, and the optimal timing and allocation between the two depends on the characteristics of the technology itself. In general, we contend that an emphasis on technology features in policy design is crucial, since it will affect the impact and effectiveness of policy measures and will be critical in the transition towards more sustainable energy systems.

3.4 Efficacy of Carbon Taxes at Early Stages of Technological Innovation

As a response to increasing scientific evidence that human activities are contributing significantly to global climate change (IPCC, 2007), considerable attention is being devoted to public policies to reduce greenhouse gas (GHG) emissions to counter climate change.

In the US, interest in carbon pricing has been rising, in part due to policy makers discouraged with the inability to pass federal cap-and-trade legislation, and attracted to the possibility of introducing a carbon tax as part of broader tax reform or as a source of new revenue to reduce budget deficits (Goulder and Schein, 2013). Many consider carbon pricing the key to achieving a reduction in GHG emissions, and providing incentives for efficient investment and consumer adoption of clean technologies. However, some make the specific case that pollution pricing is effective in encouraging technology adoption but not technological innovation.

Carbon taxes remain controversial and surrounded by considerable uncertainty, and to date have not been enacted in the US on a national scale. Aside from controversy

regarding efficacy, growth and distributional effects, estimates of the of the social cost of carbon (SCC) themselves remain highly uncertain due to the underlying uncertainties in the science of climate change science, choice of discount rates, and valuation of economic impacts (Pindyck, 2013).

In general, there exists a wide literature evaluating and comparing various environmental policy instruments, with many researchers advocating for an immediate (and at least initially low) carbon tax, even if the true SCC is unknown. Many studies compare different policy instruments and evaluate them on grounds including cost effectiveness, performance under uncertainty, distributional effects, political feasibility etc.

While almost all economic studies find a case for imposing immediate restraints on GHG emissions, the difficult and central questions remain about how much and how fast to react to the threat of global warming and reduction in GHG emissions (Nordhaus, 2007). And this remains the central issue, including at what levels will CO2 taxes be effective in a practical sense.

We contend that what is notably absent in most discussions evaluating policy instruments is a consideration of the characteristic of the technologies in question - including the stage of technology innovation, and the optimal timing and sequencing of policies in this regard. We contend that these factors will undoubtedly affect the impact of the differing policy instruments and are a crucial determinant of the effectiveness of policy instruments.

Carbon pricing has been suggested as a policy to reduce emissions by both impacting demand and encouraging the adoption of new technologies – and as some suggest even as a policy to induce technological innovation. Most argue for small CO2 tax (at least at first) even if SCC is unknown. However, to be effective in encouraging technology adoption at an early stage of technological innovation, we contend that a large CO2 tax may be needed, far larger than suggested at reasonable levels – with significant implications on distributional effects and political feasibility. We contend that if clean technologies are not commercially viable as yet, it will impact effectiveness of a realistic and plausible CO2 tax, and raise the question of alternate policy measures that may be more effective in accelerating the transition to sustainable energy systems given our current technology landscape (Chu and Majumdar, 2012).

It is in this context that we examine how effective CO2 taxes may be in reducing emissions at reasonable and plausible levels. We discuss the impact of carbon pricing on: (i) A reduction in demand, which will depend crucially on elasticities. (ii) Technology adoption, especially considering the question of the effectiveness of carbon pricing during early stages of technological innovation. (iii) Effectiveness in inducing technological change.

We contend that carbon pricing may have to be much higher than suggested plausible levels to be effective, especially with regard to technology adoption while nascent technologies are at early stages of innovation. The central question still remains how much and how fast to react to the threat of global warming, and at what levels carbon pricing will be effective (Nordhaus, 2007). We contend that policy design in this regard without consideration of alternative technologies and their stage of innovation is incomplete. And that most studies do not consider the characteristics of the technologies in question, and do not evaluate the timing and sequencing of policy instruments with the technologies in mind. We contend that carbon pricing (or consumer subsidies) when the clean technologies in question are not viable, will only be moderately effective or subsequently will need to be much higher than reasonable estimates suggest in order to have a significant impact on GHG emissions.

In general, there is an extensive literature and debate on the comparison and choice between various environmental instruments. There exists a wide literature comparing and evaluating differences between various environmental policy instruments, based on considerations of cost effectiveness, performance under uncertainty, distributional effects, and political feasibility. While it is likely that the debate regarding the relative virtues of the various instruments (e.g. carbon tax, cap and trade, hybrid approaches, etc.) will continue, yet almost all economic studies find a case for imposing immediate restraints on GHG emissions.

For example, Goulder and Parry (2008) evaluate the choice of instruments in environmental policy, and examine the tradeoffs between alternative policy measures such as emissions taxes, tradable emissions allowances, subsidies for emissions reductions, performance standards, mandates for the adoption of specific existing technologies, as well as briefly mentioning concurrent R&D and deployment policies for new "clean" technologies.

They evaluate the choice among the alternative policy instruments based on competing evaluation criteria such as economic efficiency, cost–effectiveness (along a both a narrow and broad definition of cost), distribution of benefits or costs (across income groups, ethnic groups, regions, generations etc.), the ability to address uncertainties, uncertainty and policy flexibility, political feasibility and source of government revenue, and also comment on the inherent challenges associated with obtaining a comprehensive assessment and general equilibrium impact of each instrument.

Acknowledging the basic principle in economics that pollution should be priced at the marginal external cost, suggesting that emissions taxes are superior to alternative instruments, they highlight that this may not always be sufficient or reliable because of information problems, institutional constraints, technology spillovers, and fiscal interactions.

Subsequently, they examine the strengths and weaknesses of alternative environmental policy instruments along dimension mentioned above, with several key findings: (i) No single instrument is clearly superior along all the dimensions evaluated.³⁶ (ii) Significant

³⁶ E.g. "tradable allowance systems with free allocation might perform relatively well in terms of political feasibility but relatively poorly in terms of minimizing general equilibrium costs or achieving household

trade-offs arise in the choice of instrument. E.g. ensuring a reasonable degree of fairness in the distribution of impacts, or ensuring political feasibility, often will require a sacrifice of cost-effectiveness. (iii) Hybrid instruments that combine features of various instruments in their "pure" form may sometimes be desirable. (iv) If more than one market failure is involved, it may justify (on efficiency grounds) employing more than one instrument.

However, notwithstanding their claim that no single instrument is superior to all others in all settings, they find that the instrument choice literature makes a strong case for the wider use of flexible, incentive-based policies (e.g. emissions taxes, tradable emissions allowances, subsidies for pollution abatement, and taxes on inputs/goods associated with emissions) rather than direct regulatory instruments (e.g. technology mandates and performance standards).

Evaluated in terms of cost effectiveness, they find that the most cost-effective instruments (under the narrow definition of "cost") are those that price the pollution externality directly (e.g. emissions taxes and tradable emissions permits). And that other price instruments are less cost-effective because they fail to optimally exploit all the major channels for emissions reductions. In addition, direct regulatory instruments also fail to optimally engage all of the major pollution reduction channels and, if non-tradable, fail to equate the marginal costs of emissions reductions across heterogeneous firms.

Evaluated in terms of uncertainty and an instrument's ability to adjust to new information, they find that in a static context, the relative efficiency impact of a pricing policy as compared to a quantity policy depends on the relative steepness of the aggregate marginal abatement cost curve and the marginal damage curve (Weitzman, 1974). In general these results carry over to a dynamic setting, where environmental damages depend on the accumulated stock of pollution. However, they state that some dynamic analyses (Kolstad, 1996; Pizer, 2002; Newell and Pizer, 2003) suggest that in the presence of uncertainty, a carbon tax might offer substantially higher expected efficiency gains than a cap-and-trade system.

Regarding distributional impacts (in particular across household income groups) and the related issue of political feasibility, they find that the ultimate impacts of revenue-raising policies such as emissions taxes and auctioned emissions allowances depend critically on how the revenues are used³⁷. And that a fairer distributional burden could be achieved through recycling revenues from carbon taxes or auctioned carbon allowances via tax reductions favoring low-income groups (Dinan and Rogers, 2002; Metcalf, 2007). In contrast, free allocation would tend to increase the disparity in the burden-to-income

equity. The opposite applies for (revenue-neutral) emissions taxes or auctioned allowances. Direct regulatory policies have some appeal in terms of distribution but are generally less cost-effective along other dimensions. Emissions taxes and auctioned allowances may lose some of their key attractive properties if accompanying legislation does not require offsetting reductions in other taxes." (Goulder and Parry, 2008).

³⁷ Since these affect low income groups disproportionately.

ratios between low- and high-income groups, since firms' equity values (and subsequently that of upper-income groups) would rise with the increase in producer surplus (Dinan and Rogers, 2002). In this regard, direct regulatory policies may have some appeal since they avoid transferring rents from households (through large price increases) to firms.

In general, despite the inherent challenges associated with a complete assessment of policy impact (including GE effects and the subjective emphasis placed on competing criteria), and notwithstanding the fact that no single instrument is superior to all others in all settings, they make a strong case for the wider use of flexible, incentive-based policies to reduce emissions. In addition, they *briefly* discuss the rationale to supplement emissions control policies with technology focused policies which directly promote the invention or deployment of new technologies.

In contrast, Goulder and Schein (2013) focus specifically on the comparison and choice between carbon taxes and cap and trade policies to reduce GHG emissions, based on the main advantage of emissions pricing policies (e.g. carbon taxes and "cap and trade") being their potential to achieve emissions reductions at lower cost than is possible under direct regulations (e.g. mandated technologies or performance standards)³⁸.

They evaluate the distinguishing features between the two policy instruments, claiming that arguments stating that carbon taxes are superior to cap and trade in terms of the incentives for reducing emissions, distributional impacts, options for employing or avoiding offsets, and potential for safeguarding international competitiveness are unfounded. And that if properly designed, the two approaches have equivalent potential along each of these dimensions, however this does depend critically on the specifics of the design (which they state is as important as the choice of instrument itself).

They state that when comparably designed, a carbon tax, cap-and-trade system, and hybrid policy yield very similar incentives to reduce emissions. Comparably designed systems also imply the same distribution of policy costs across households or firms (depending on whether firms are allowed intra-marginal emissions without charge and the way revenues from auctioned allowances or carbon taxes are spent). In addition, the different policy tools have similar capabilities for mitigating potential adverse impacts on the international competitiveness of carbon-intensive domestic firms (depending on whether the policies are introduced upstream or downstream, and the extent to which provisions for border adjustments or output-based subsidies are included).

However, they do find that along other dimensions, the alternatives perform differently. While no one approach dominates (with the ranking ultimately dependant on the emphasis one places on the different criteria) yet, they find that interestingly the carbon

³⁸ They also briefly touch upon the varying perspective amongst academic researchers e.g. Keohane (2009) and Stavins (2007) favor cap and trade, while Metcalf (2007) and the "Pigou Club" formed by Harvard's Greg Mankiw prefer a carbon tax.

tax or hybrid seem to score better along the dimensions where the advantages or disadvantages are unambiguous. Interestingly, they further find that many of these advantages stem from the exogeneity of the allowance prices – which are likely to minimize expected policy errors in the face of uncertainties, prevent emissions price volatility, help avoid problematic interactions with other climate policies, and avoid large wealth transfers to oil exporting countries.

In general, while the debate between the choice of instrument is likely to continue, nonetheless, they state that the virtues shared by all three instruments is that "each approach is a form of emissions pricing and, as such, each provides flexible and permanent incentives for emissions abatement that are absent in other forms of regulation. All three approaches have the potential to bring about greenhouse gas emissions reductions in a way that is cost-effective and equitable as well as environmentally successful" (Goulder and Schein, 2013).

While the debate is likely to continue, almost all economic studies find a case for imposing immediate restraints on GHG emissions, with many researchers advocating for an immediate (and at least initially low) carbon tax even if the true SCC is unknown. However once again, the difficult and central question ultimately remains about how much and how fast to react to the threat of global warming and reduction in GHG emissions (Nordhaus, 2007).

For example, Pindyck (2013) argues for an immediate carbon tax even if the true SCC is unknown. Based on the widely acknowledged fact that the true marginal social cost of burning a ton of carbon to society is greater that its marginal private cost, thereby imposing an externality on society which the consumer or firm should internalize, he advocates for imposing an immediate carbon tax on emissions (or adopting a similar policy such as cap-and-trade).

He states, the only issue remains regarding the disagreement about the correct SCC due to certain fundamental challenges associated with its estimation. Subsequently there remains wide disagreement regarding the level of carbon pricing – with some on one end of the spectrum suggesting a small CO2 tax of about \$10/ton CO2 (approx 10cents/gallon gasoline), arguing that increases in global temperatures will be moderate, in the distant future, and only with small economic impact. However, on the other end of the spectrum, others argue for immediate and stringent CO2 policy based on the possibility of dramatic temperature increases with catastrophic effects, thereby implying a large SCC of \$100 - \$200/ton CO2 (equivalent to approx \$2/gallon gasoline).

Pindyck (2013) outlines the fundamental reasons for this disagreement regarding the SCC as based on the uncertainties surrounding climate change, i.e. uncertainties in the science of climate change, choice of discount rates (on which the IAMs are highly dependent), and valuation of economic impacts. In particular, he states that the uncertainty over the likelihood of alternative climate outcomes and their impact remain fundamental challenges. In addition, there are uncertainties surrounding the framework to be used to

evaluate the benefits from GHG abatement, including the social welfare function and discount rate to value benefits occurring in the distant future.

In addition, he argues that current IAMs remain unable to provide meaningful estimates of SCC, as they suffer from two major flaws: (i) The treatment of economic impact (e.g. loss functions relating temperature increases to reductions in GDP) is ad hoc, not based on economic theory, and has little predictive value. (ii) IAM simulations ignore the possibility of a catastrophic climate outcome, in terms of a very large economic effect – without which one cannot have meaningful estimates of the SCC.

In general, the challenges in estimating the true SCC remain non-trivial (since we have no data to yield estimates of how likely catastrophic outcomes are), which is why most analysis is based on *plausible* events, but which ignore catastrophic outcomes which should be of concern. Which is why Pindyck (2013) asserts that \$21/ton CO2 or \$65/ton CO2 estimates may provide a reasonable estimate of "most likely outcomes" and plausible events, but fail to assess more extreme outcomes and capture the possibility of catastrophic climate outcomes - which might lead to a SCC as high as \$100-\$200/ton CO2.

However, despite the uncertainties, his policy recommendation is not to delay action and impose and immediate carbon tax (or equivalent policy) by taking the \$20/ton CO2 Interagency Working Group estimate as an initial, rough and politically acceptable lower bound even if it may not be the true SCC^{39} – based on the fact that there is a social cost of carbon, which may be uncertain but is positive. And primarily because it is should be established that there *is* a social cost of carbon, which should be internalized in the prices that consumers and firms see and pay. He concludes that the carbon tax can later be increased or decreased accordingly as we obtain a better understanding of the uncertainties surrounding of climate change and its impacts.

Similarly, Baumol & Oates (1971) argue for immediate carbon pricing and acceptability standards despite not knowing optimal SCC level, based on a similar theoretic justification of the regulation of externalities by imposing unit taxes (or subsidies) to control emissions externalities⁴⁰, as the market will in general not generate appropriate levels of outputs where market prices fail to reflect the social damages/benefits associated with certain activities.

However they acknowledge the practical challenges and inability to measure the marginal social damage associated with this approach. As with most authors, they point out that we do not know how to calculate the ideal tax or subsidy levels in practice. Subsequently they advocate the idea of establishing a practical substitute approach, representing a close approximation which may not results in an optimal allocation of resources, but does

³⁹ Or push for a substantial tax that would lead to a large reduction in emissions on the grounds that we need an "insurance policy" against a possible catastrophic outcome.

⁴⁰ By equating the tax on emissions activities equal to its marginal social cost.

possesses some important optimality qualities while avoiding having to resort to direct controls.⁴¹

As a practical solution, they propose setting a set of environmental quality standards (i.e. admittedly arbitrary and subjective acceptability standards), followed by the imposition of taxes on related emissions sufficient to attain these standards (rather than taxes based on the unknown value of marginal net damages). This could be followed by an iterative adjustment in tax rates, such that with experience, appropriate tax levels for the achievement of a target reduction in pollution could be obtained (with the hope that this would be a convergent, iterative process – however they acknowledge that it is unclear whether this sequence would in fact converge toward the optimal taxes and resource allocation patterns). While this would not lead to Pareto efficient levels of the relevant activities and allocation of resources, it would be the least-cost method to realize the specified targets (rather than e.g. the optimal level of pollution) despite the arbitrary character of the acceptability standards selected.

In an international context, Nordhaus (2007) advocates for internationally harmonized carbon taxes (HCT) as an approach to help countries coordinate their policies to slow global warming, suggesting that price-type approaches such as HCTs are more effective and efficient instruments for coordinating policies and slowing global warming, than quantity approaches like those found in the Kyoto Protocol. He performs a comparison of price and quantity approaches based on the relationship to ultimate economic and environmental targets, performance under uncertainty, volatility of induced carbon prices, potential for corruption, and ease of implementation. And he concludes that price-type approaches such as carbon taxes have major advantages for slowing global warming - while acknowledging that this approach is unfamiliar in international environmental agreements, that taxes are unpopular, and that they don't impose explicit limits on the GHG emissions growth or concentrations.

While identifying the fundamental obstacles that any international climate change regime faces, including the distribution of emissions reductions across countries and the participation of low income countries - he focuses on the most crucial one as being the question of the "optimal" level of emissions reductions⁴². Consistent with the previous authors, he states that this is undoubtedly the most difficult and controversial question in the economics of global warming, and that any estimate of the efficient carbon tax is unlikely to capture all the nonmarket aspects of global warming, the problems of uncertainty and risk aversion, as well as the potential for "dangerous interferences" with many global processes.

However, he strongly advocates for a HCT as it is a recognition that countries care about economic development and the future costs of global warming. Regarding the appropriate level of carbon pricing, he cites the relatively low current efficient market price of carbon found in the RICE model - which he states was one of the major

⁴¹ And the associated inefficiencies associated with direct controls, including real higher enforcement costs.

⁴² I.e. the level and trajectory of emissions reduction

conclusions in a review of IAMs, namely that modest controls are generally optimal (Kelly and Kolstad, 1999). And he advocates that the tax start relatively low and then rise steadily over time, i.e. that countries would set market penalties on GHG emissions at levels that are equalized across different regions and industries. And that the tax would start relatively low and then, unless the outlook changes for better or worse, rise steadily over time to reflect the increasing prospective damages from global warming.⁴³

While most studies advocate for an (at least initially) low carbon tax, the UK Government's Stern Review (2007) has a strikingly different conclusion from mainstream economic models, and argues for urgent, extreme and immediate reductions in GHG emissions on the basis that damages from climate change are large – resulting in the high end of SCC estimates of \$310 per ton of carbon. Nordhaus (2007) however calls the review into question and finds that this very unambiguous and radical policy recommendation depends decisively on assumption of a near zero discount rate combined with a specific utility function which is not robust to the substitution of assumptions.

In an analysis of the Stern Review on the Economics of Climate Change Nordhaus (2007) maintains that "it is a simple economic insight...that it is critical to have a harmonized carbon tax or the equivalent both to provide incentives to individual firms and households and to stimulate research and development in low-carbon technologies.....And that carbon prices must be raised to transmit the social costs of GHG emissions to the everyday decisions of billions of firms and people." However, he states the crucial question remains regarding how much and how fast we should react to the threat of global warming, and that there is a wide disparity in estimates with the Stern Review's radical proposal of SCC being at the high end.

He calls the fundamental assumptions of the Stern Review into question and finds that the Review's very low discount rates lie at the heart of the striking results and the need for immediate actions to reduce GHG emissions sharply. Combined with other assumptions, this magnifies impacts in the distant future and rationalizes deep cuts in emissions and consumption.

However, substituting these assumptions with more conventional ones used in other analyses, he states that the Review's conclusions disappear, resulting in the familiar climate-policy ramp in which policies to slow global warming increasingly tighten over time. A climate- policy ramp with modest rates of emissions reductions in the near term, followed by sharp reductions in the medium and long term. However, with the exact mix and timing of emissions reductions depending upon details of costs, damages, and the extent to which climate change and damages are nonlinear and irreversible.⁴⁴

⁴³ "Because carbon pricing would be equalized across countries, the approach would be spatially efficient among those countries that have a harmonized set of taxes. If the carbon tax trajectory follows the rules for "when efficiency," it would also satisfy inter-temporal efficiency" (Nordhaus, 2007).

⁴⁴ "The logic of the climate-policy ramp is straightforward. In a world where capital is productive, the highest-return investments today are primarily in tangible, technological, and human capital, including research and development on low-carbon technologies. In the coming decades, damages are predicted to rise relative to output. As that occurs, it becomes efficient to shift investments toward more intensive

Despite the Stern Review, Nordhaus (2007) finds that the central and fundamental questions regarding the economics of climate change and environmental policy still remain unanswered - namely how much and how fast to react to the threat of global warming, and how costly it will be.

It is in this context that we examine how effective reasonable and plausible levels of carbon pricing, as suggested by the general literature, may be in reducing emissions in a practical sense. This will be driven by three factors: (i) A reduction in demand, which will depend crucially on elasticities. (ii) Technology adoption, especially considering the question of the effectiveness of carbon pricing during early stages of technological innovation. (iii) CO2 effectiveness in inducing technological change.

Firstly, the price elasticity of demand for e.g. oil will determine how effective a reasonably priced carbon tax will be in reducing emissions. With a low price elasticity any moderately priced carbon tax will not have much of an impact on demand, and is not going to be an effective policy for reducing carbon emissions.

As observed by Ozimek (2011), estimates of price elasticities vary, however Davis and Killian (2011) state that even under the largest plausible estimates, tax increases of the magnitude that are being discussed will have only a moderate short-run impact on total US gasoline consumption and carbon emissions based on their estimates. Long-run elasticities may be larger, but standard econometric models based on historical data do not allow the prediction of such long-run effects⁴⁵.

Estimates vary, and on the low end a recent IMF study (2011) estimated a long-run price elasticity of oil demand as -0.035 – which is lower than found in the results of several literature reviews of oil and gasoline price elasticities as shown by Hamilton (2008) (table 3.1).

emissions reductions. The exact mix and timing of emissions reductions depend upon details of costs, damages, and the extent to which climate change and damages are nonlinear and irreversible" (Nordhaus, 2007).

⁴⁵ Similarly, The International Handbook on the Economics of Energy states that "The past is not necessarily a good guide to the future in this area, and it is possible that the very long-run response to price changes may exceed those found in empirical studies that from relatively short time periods."

Study	Product	Method	short- run price elasticity	long-run price elasticity	long-run income elasticity
Dahl and Sterner (1991)	gasoline	literature survey	-0.26	-0.86	1.21
Espey (1998)	gasoline	literature survey	-0.26	-0.58	0.88
Graham and Glaister (2004)	gasoline	literature survey	-0.25	-0.77	0.93
Brons, et. al. (2008)	gasoline	literature survey	-0.34	-0.84	
Dahl (1993)	oil (developing countries)	literature survey	-0.07	-0.30	1.32
Cooper (2003)	oil (average of 23 countries)	annual time- series regression	-0.05	-0.21	

Table 3.1 - Review of Oil and Gasoline Price Elasticities Source: Hamilton (2008)

However, several recent studies contend that the price elasticity of demand has decreased in the past decade, including a study by Hughes, Knittel, and Sperling (2008) who find short-run gas price elasticity estimates of -0.034 to -0.077 for 2001-2006 compared to the much larger estimates of -0.21 to -0.34 for 1975-1980. Notably, while these recent estimates may be larger than the IMF numbers, they are nevertheless low.

On a technical note, while the evidence does seem to suggest that more recent estimates are better than earlier ones, Davis and Killian (2011) state that they may still underestimate long run elasticities and should be treated with caution, highlighting several challenges associated with the measurement of the average price elasticity: (i) The response of demand to price changes may be asymmetric, with price increases causing a larger response to demand than price decreases – since price increases may be more likely to cause shifts to newer, more energy efficient technologies while price decreases are unlikely to undo such shifts. This would result in estimates of the average price elasticity to be a downward biased estimate for the response to price increases. (ii) The estimates shown are for the price elasticity of demand, and not the tax elasticity of demand, for which the consumption response is likely to be more persistent and may induce a larger behavioral response. (iii) Difficulties in estimation due to e.g. joint determination of price and quantity demanded such that single equation or panel data methods (like in the IMF estimates) may bias estimates towards zero. (iv) The sensitivity of the elasticity estimates to econometric misspecification. They illustrate this by examining U.S. state level demand for gasoline to demonstrate how sensitive elasticity estimates are to econometric misspecification, and derive estimates of the elasticity from -0.10 (single equation model) to -0.19 (panel data model) and lastly -0.46 (using changes in state level gas taxes as an instrument) - illustrating considerable variation in estimates.

Nonetheless they conclude that despite their results – even under the largest plausible estimates, tax increases of the magnitude that are being discussed would have only a moderate short-run impact on total US gasoline consumption and carbon emissions based on their estimates.

Secondly, the stage of technological innovation and subsequent technology readiness will determine how effective a reasonably priced carbon tax will be in encouraging clean technology adoption and emissions. With many clean technologies currently not commercially viable, a moderately/reasonably priced carbon tax may not have much of an impact on technology adoption and may not be an effective policy for reducing carbon emissions.

A recent technology adoption study by Firestone and Marnay (2006) states that a carbon tax greater than \$500/ton Carbon (equivalent to \$136/ton CO2) would be required to incent significant adoption of carbon-free renewable energy based on the current state of technology. Using a Distributed Energy Resources (DER) Customer Adoption Model in which they simulate technology adoption, costs, and carbon emissions, they examine the question of the choice of economically optimal DER technologies for US commercial buildings across different cities, under a carbon tax.

They simulate the technology adoption of DER, which include a range of energy conversion and storage technologies for improved carbon efficiency, including combined heat and power (CHP), small-scale power generation (e.g. solar technologies), thermal and electrical storage (e.g. batteries and thermal tanks), and thermally activated cooling - all of which can reduce the carbon-intensity of meeting end-use energy loads.

The output of their model under varying carbon tax scenarios includes optimal DER investment and technology adoption, optimal operating schedule, electricity and natural gas consumption and carbon emissions attributed to energy consumption. The results of their simulation indicate that carbon taxes have little effect on investment behavior and almost none on carbon emissions in SF, while results in Boston indicate that a realistic carbon tax level (\$100/ton Carbon) incents less than one percent carbon reduction. Overall, they conclude that a realistic carbon tax (\$100/ton Carbon equivalent to \$27.25/ton CO2) is too small to incent significant carbon reducing effects on economically optimal DER adoption. And that in general, a carbon tax greater that \$500/ton Carbon (equivalent to \$136/ton CO2) would be required to incent significant adoption of carbon free renewable energy.

Similarly, Torani, Rausser, and Zilberman (2014) examine the question of how to transition towards a meaningful percentage of solar PV energy in a sustainable manner, and which policies are most effective in accelerating adoption of solar PV technologies. They develop a stochastic dynamic real options model of the adoption of solar PV in the residential and commercial sector, evaluating the threshold and timing of the consumer's optimal investment decision given two sources of uncertainty, and obtain a cumulative
likelihood and timing of substitution amongst energy resources and towards solar under plausible rates of technological change, electricity prices, subsidies and carbon taxes.

Based on their specification, their results indicate that there may be a displacement of incumbent technologies, and a widespread shift towards solar PV in the residential and commercial sector in under 30 years. However, this can occur independent of downstream incentives and carbon pricing policies (at \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2) – which have a decidedly modest impact in accelerating adoption, at least at levels up to \$150/ton CO2 and may not be an effective part of climate policy in this regard⁴⁶.

Instead, their results demonstrate that further technological change is the crucial determinant and main driver of adoption, outweighing the effect of subsidies and taxes (at levels up to \$150/ton CO2). The results demonstrate that R&D support and further technological change is the crucial determinant in accelerating widespread adoption of solar PV - suggesting that subsidies and taxes don't make a substantial difference in a technology that's not commercially viable, while research does. This further suggests that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant and main driver of a widespread transition to solar and plausibly other backstop technologies – and that it should play an increased role in climate policy.

They state that their results do not imply that carbon pricing shouldn't play a role in climate policy in general. Carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies – however it has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2. Suggesting, that if a widespread transition to solar energy is likely to happen in this sector, it will be because of R&D and technological advancement.

Similarly, Williams et al. (2012) examine the technology and policy path needed to achieve deep GHG emissions cuts by 2050 and find that widespread electrification of transportation and other sectors will be required, and argue for an expanded role for aggressive R&D policies, as well the need for technology and policies to be deployed in a coordinated manner such that emission reduction benefits are achieved at an acceptable cost.

In their study they conduct modeling of the physical energy and economic transformation to obtain a realistic technology and policy roadmap required to meet the aggressive targets that certain states and countries have adopted for deep reductions in GHG emissions by 2050.

⁴⁶ Further, their results indicate that subsidies and taxes become increasingly ineffective with higher rates of technological change.

Specifically, they analyze the infrastructure and technology path required to meet California's goal of an 80% reduction below 1990 levels⁴⁷, and the specific changes in infrastructure, resources, technology, cost, and governance required for energy transition and to decarbonize CA economy. Crucially, they attempt to bridge the gap between planning for shallower, near-term GHG reductions, based entirely on existing commercialized technology, and deeper, long-term GHG reductions, which will depend substantially on technologies that are not yet commercialized⁴⁸ – based on learning curves comparable to those in other studies.

They find that technically feasible levels of energy efficiency and decarbonized energy supply alone will not be sufficient to achieve the aforementioned targets, and that widespread electrification of transportation and other sectors will be required to do so. Decarbonized electricity will play a pivotal role and become the dominant form of energy supply - requiring a transformation that demands technologies that are not yet commercialized, as well as coordination of investment, technology development, infrastructure deployment and policy roadmap.

Their results indicate three main energy system transformations necessary to meet the target of reducing GHG emissions 80% below 1990 levels by 2050: (i) End use EE must be improved aggressively. (ii) Electricity supply has to be nearly decarbonized, with renewable energy, nuclear, and fossil fuel with carbon capture and storage (CCS) each having the potential to become the principal long-term electricity resource in CA - however with all currently suffering from technical limitations and high costs. (iii) Most existing direct fuel uses (e.g., gasoline in cars) have to be electrified. There is no alternative to widespread switching of direct fuel uses to electricity in order to achieve the reduction target. They state that without electrification, the other measures combined would produce at best 2050 emissions of about 50% below the 1990 level. Additionally, the largest share of GHG reductions from electrification would need to come from the transportation sector. This result is corroborated by a recent report on achieving 80% GHG reductions in the EU which found that similar transformations were required, including electrification of transportation and buildings.

With the pivotal role of electricity as the dominant component of the 2050 energy economy, the cost of decarbonized electricity becomes a paramount economic issue. And they estimate that generation mixes dominated by renewable energy, nuclear, and CCS, in the absence of cost breakthroughs, will raise the present average cost of electricity generation by a factor of about 2.

⁴⁷ California's Assembly Bill 32 (AB32) requires the state to reduce GHG emissions to 1990 levels by 2020, which is a reduction of 30% relative to business-as-usual assumptions. California has also set a target of reducing 2050 emissions 80% below the 1990 level, consistent with an Intergovernmental Panel on Climate Change (IPCC) emissions trajectory that would stabilize atmospheric GHG concentrations at 450 parts per million carbon dioxide equivalent (CO2e) and reduce the likelihood of dangerous anthropogenic interference with the climate (Williams et al., 2012).

⁴⁸ With technology penetration levels within the range of technological feasibility for the United States suggested by recent assessments, i.e. they did not include technologies expected to be far from commercialization in the next few decades, such as fusion based electricity.

Subsequently their two main policy recommendations are: (i) It is crucial that these technologies and systems are commercially ready. Minimizing the cost of decarbonized generation should be a key policy objective, with some estimates indicating that aggressive R&D policies could reduce the cost of low-carbon generation in the United States from 2020 to 2050 by about 40% or \$1.5 trillion. (ii) Technology and policies must be deployed in a coordinated manner such that the emission reduction benefits are achieved at an acceptable cost. E.g. "switching from fuels to electricity before the grid is substantially decarbonized negates the emissions benefits of electrification; large-scale deployment of electric vehicles without smart charging will reduce utility load factors and increase electricity costs; and without aggressive EE, the bulk requirements for decarbonized electricity would be doubled, making achievement of 2050 goals much more challenging. Thus the logical sequence of deployment for this transformation is EE first, followed by decarbonization of generation, followed by electrification of most direct uses of oil and gas."

They conclude that this transition crucially requires mobilizing investment and coordinating technology development and deployment on a very large scale over a very long time period. How best to achieve this currently a source of active debate regarding the roles of markets, government, carbon pricing, and R&D policy. But their policy recommendation regarding R&D funding, and technology and policy coordination and sequencing is pertinent, and raises the question of how best to enable the transition towards clean energy systems and which climate policy modalities will be most effective.

Thirdly, some researchers make the case that carbon pricing is effective in encouraging technological innovation in addition to technology adoption. However in general, there is considerable uncertainty and disagreement regarding this issue, in addition to how the possibility of induced technological change may affect the optimal timing and extent of carbon emissions abatement and the optimal time path of carbon taxes.

Some researchers have recently emphasized that CO2 policies and the rate of technological change are connected, in the sense that the price of carbon-based fuels affects incentives to invest in research and development (R & D) of alternative technologies. In addition, climate policies can affect the technology development through impacts on LBD to the extent that these policies affect producers' experience with alternative energy fuels or energy-conserving processes, they can influence the rate of advancement of knowledge. Thus, through impacts on patterns of both R & D spending and LBD, climate policy can affect technological innovation and change (Goulder and Mathai, 2000).

However, other researchers have made the specific case that while pollution pricing may be effective in encouraging technology adoption it is not effective in encouraging technological innovation (Williams et al., 2012).

Goulder and Parry (2008) state that achieving the aggressive goal of reducing GHG emissions by 80 percent below their 1990 levels by 2050 at reasonable cost will require more than substitution among known technological processes - it will necessitate major

technological breakthroughs. Technological breakthroughs, which emissions control policies such as carbon pricing may be incapable of bringing about since they provide invention incentives only indirectly—by emissions pricing or by raising the costs of conventional, "dirty" production methods through direct regulation. In addition, the existence of additional market failures associated with technology innovation (e.g. the appropriability problem) implies that incentives for clean technology R&D will be inefficiently low, even if pollution externalities are appropriately priced.

They find, that the theoretical and empirical literature comparing the efficiency of alternative environmental policy instruments in promoting the development of cleaner technologies (Jung et al., 1996; Fischer et al., 2003; Milliman and Prince, 1989) generally points towards the fact that no single instrument can effectively correct market failures from both emissions externalities and the knowledge appropriability problem – and that multiple market failures justify multiple instruments. Indeed, achieving a given emissions reduction through one instrument alone involves considerably higher costs than employing two instruments, and that e.g. imposing stiffer emissions prices than warranted by environmental externalities alone is an inefficient way to promote innovation (Fischer and Newell, 2008; Schneider and Goulder, 1997).⁴⁹

In general, the debate is likely to continue regarding how effective carbon pricing is in inducing technological change and innovation. And subsequently, how the potential of policy-induced technological change may impact the design of carbon-abatement policies, including the optimal timing and extent of carbon emissions abatement as well as the optimal time path of carbon taxes (Goulder and Mathai, 2000).

3.5 Deployment Policies and Learning-By-Doing

In general, there are strong arguments for technology innovation policies in addition to instruments aimed at curbing emissions. However, while most researchers agree that additional policies are warranted to support basic and applied research⁵⁰, there is less agreement regarding the justification for policies intended to promote technology deployment. Crucially, we contend that deployment policies are justified, depending on the specific industries, processes, characteristics of the technology, stage of the technology innovation, LBD potential, and assumptions about consumer behavior.

While investments in public R&D can initiate and support the development of new energy technologies, a focus on solely on publicly funded R&D and development efforts

⁴⁹ They state that this not only generates excessive short-term abatement, but it also fails to differentiate among technologies that may face very different market impediments. E.g. alternative automobile fuels and carbon capture and storage technologies might warrant relatively more support than other technologies, to the extent that there are network externalities associated with the new pipeline infrastructure required to transport fuels to gas stations, or emissions associated with underground storage sites.

⁵⁰ Although the specific instruments and level of support are less clear.

without emphasizing the role of deployment efforts and LBD is incomplete (Sagar et al., 2006). It is widely acknowledged that the process of technical change involves LBD and the improvement of performance over time which is a product of experience which arises from cumulative installed capacity (Arrow, 1962), and without which one often can't progress.

Consequently, deployment efforts can play a crucial role in the commercialization of new energy technologies. They can help address factors that hinder widespread implementation of technologies, including cost, infrastructure needs, market barriers, information and financing constraints (IEA, 2000; IEA, 2003; Sagar, 2004), requiring public sector responses to encourage early adoption of new technologies through targeted policy incentives to help overcome these barriers. Public sector responses and effective early deployment efforts can be achieved through subsidies to favorable technologies, technology based and performance based standards, mandates, government procurement programs, and some argue even pollution charges and cap and trade. Notably, the relative emphasis of the various approaches may depend in part on the characteristics of the technology itself.

In general, it is held that LBD justifies commercialization subsidies if and only if external economies and spillovers arise from private experience (Kemp, 1964). In addition, Goulder and Parry (2008) find that policies to promote clean technology development and deployment are justified on efficiency grounds to the extent that they can address market failures beyond the pollution externality including: (i) An appropriability market failure which could arise in connection with the deployment of new technologies. Specifically, early adopters of a new technology could achieve lower production costs for the new technology over time – which would award external benefits to later adopters of the technology and might justify short-term assistance for adopting the new technology. However, as the potential for deployment-related knowledge spillovers may vary depending on the technology, deployment policies would have to be evaluated along this dimension to be justified. (ii) A market failure relating to consumer valuation of energyefficiency improvements, which consumers may systematically undervalue. They state that possible evidence for this is the tendency of consumers to require very short payback periods for durable energy-using equipment – effectively applying discount rates significantly above what might be considered the social discount rate (Marglin, 1963). Hence implying, that from a social welfare perspective, consumers tend to discount the future too heavily in their choices of consumer durables (or more broadly in their saving decisions), thus providing a rationale for government support.

However any discussion of deployment policies must include mention of the broader need to deconstruct and improve our understanding of the LBD mechanism itself in order to enhance learning gains. Learning is not an automatic byproduct of cumulative installed capacity, and we do not yet have a clear understanding what leads to experience and learning gains. In this context, it is crucial that we both increase our understanding of the learning process as well as the integration between the complementary stages of R&D and LBD and the feedback loops between them – which may help in technology refinement and lead to more improvements and breakthroughs as both are essential elements of technological change.

In addition, the timing, sequencing and duration of appropriate policies is a pertinent issue. Given that investments for both R&D and learning are needed for technological change, balancing R&D and deployment investments, and the optimal allocation between the two becomes a pertinent issue, which we contend depends in part on the characteristics of the technology (Sagar et al., 2006; Torani, Rausser, and Zilberman, 2014). Optimal utilization may require a different split between R&D and deployment (LBD) policies for different technologies, based on the estimated and potential gains achievable through R&D efforts as well as through deployment/LBD.⁵¹ We emphasize that this depends crucially on the characteristics of the technology, and the stage it is in - and that these considerations should guide energy policy. Not surprisingly, we contend that the technology under consideration mostly determines how and when to allocate available funds. E.g. Sagar et al. (2006) contend that while fuel cells are advanced enough that they should be subject to both types of investment, a technology like fusion energy (with an operable commercial prototype likely half a century away) still requires only R&D investments.

Notably, we contend that the promotion of the deployment of emerging energy technologies has a crucial role to play in the process of learning and to help overcome initial cost and infrastructure barriers. If the innovation process involves LBD potential, unless firms have a sufficient volume of experience or a significant client base they will not invest in a technology, which will deter learning. Hence deployment policies, and taxes and subsidies are not a value by themselves, but provide an incentive for adoption that enhances learning and are justified provided a LBD potential exists. However we contend that the key to deployment subsidies is that they must be short lived, and provided for a limited amount of time to be effective, otherwise they won't prevent delay.

Preventing delay is a crucial element of deployment policies, therefore any subsidy has to be short lived. Otherwise, because of rational expectations, people will delay investment and adoption of the nascent technology, i.e. if a consumer knows that fuel cell cars will become cheaper (due to technological change), they will delay the investment and wait. Hence, in some regard, preventing delay is a public good and the government's role will remain crucial.

This dynamic is illustrated in Torani, Rausser, Zilberman (2014), in which they develop a real options model of the optimal threshold and timing of the consumer's adoption of solar PV in the residential and commercial sector given uncertainty in both the price of electricity and the cost of solar. Although their study relates specifically to solar PV, they

⁵¹ And while R&D typically precedes deployment, it may be justified to undertake them simultaneously or iteratively to exploit the possible interaction between the two – depending on the technology under consideration and its R&D and LBD potential.

provide a general framework to evaluate investments in competing alternative renewable energy technologies.

ROA is fundamentally a stochastic dynamic framework analyzing investment decisions in the presence of uncertainty of the economic environment, irreversibility of the investment decision, and most importantly, the ability to postpone the investment decision (Dixit and Pindyck, 1994). While traditional static "now or never" net present value (NPV) breakeven models of investment have resulted in predictions that have been observed to overestimate investment and adoption - a key result of the real options framework is that in light of these three factors, the investor will require a significant excess return above the expected present value before making the investment.

Specifically, while a general result of the real options model has been to illustrate the effect of increased uncertainty on delaying investments, they extend the analysis to illustrate a significant dynamic that emerges - which provides further insight into the differing paradigms of the NPV and ROA models of investment. Namely, that a high rate of technological innovation/change in the new technology delays adoption in ROA if the consumer has rational price expectations - resulting in an increase the excess return required by the consumer before she is willing to give up the option to invest, and commit to the investment.

This is illustrated in figure 3.3 in terms of the k* threshold ratio, indicating that the consumer will adopt later, at a higher price of electricity for a given cost of solar, with a higher rate of technological innovation i.e. she demands a higher premium before adopting the nascent technology.



Fig. 3.3: k* Separating Region of Adoption and Waiting

This is a counterintuitive result of increased funding, R&D productivity and technological change, which are ultimately intended to promote adoption. However it is entirely intuitive - if the rate of cost decline increases, waiting instantly becomes more valuable and giving up the option to wait becomes more costly, hence the user will require a higher premium to give up this option. This finding is entirely consistent with the energy efficiency gap observed in consumer behavior.

Intuitively, this result signifies that the consumer will postpone adoption to reap the benefits of further technological change in e.g. solar as long as certain conditions apply⁵². By comparison, the NPV threshold of investment remains unchanged irrespective of the rate of technological change, since it is a static "now or never" proposition and doesn't consider the option of postponing the investment decision waiting for further technological change in the nascent technology before making the investment. In other words, because of the expectation of further technological change and future cost reductions, consumers will delay adoption of the nascent technology.

This is entirely consistent with the energy paradox, and the inclination of households and firms to require very high internal rates of return in order to make energy saving investments. Ansar and Sparks (2009) use a stochastic OV model (focusing on the irreversibility, the uncertainty of their future payoff streams, and the investor's anticipation of future technological advances, and the ability to delay the investment decision) and similarly find that delay allows the potential investor to cash in on future experience-curve effects which is a fundamental reason why households and firms delay making energy saving investments until internal rates of return exceed values of 50% and higher, consistent with observations in the economics literature.

In terms of the implications on deployment policies, this dynamic implies that if given a permanent subsidy, people will delay adoption because of the expectation of technological change and cost reductions, and subsidies will not be as effective in encouraging adoption, deployment and learning. However, a limited time subsidy which is credible can counter the Dixit and Pindyck effect and the delay incentive. We contend that to be effective, deployment subsidies which reduce the initial cost need to be short lived and tend to expire – in order to aim to counter the Dixit Pindyk effect.

Alternatively, one could avert this delay dynamic with a high commercialization subsidy or a high tax. However in the case of Solar PV, at its current state of technology and cost, Torani, Rausser, and Zilberman (2014) show that both subsidies and taxes would need to be higher than reasonable/plausible levels discussed in the literature (e.g. \$150/ton CO2) to be effective at this stage. This is due to the expectation of future technological advances and cost reductions, the Dixit and Pindyck delay factor, as well as the fact that

⁵² Namely that it isn't prohibitively expensive to do so, i.e. as long as the price of electricity is not increasing at an increasing rate (in present value terms) while postponing the investment. One will postpone adoption if the price of electricity and cost of solar are both decreasing at a decreasing rate. Irrespective of the relative magnitudes of the rates of change and by virtue of their signs, the rate of decay of the cost of solar is greater than that of the price of electricity, in present value terms.

the technology is presently not commercially viable relative to traditional sources of electricity generation.

Crucially, deployment subsidies are justified since they may provide an incentive for adoption that enhances learning – and they are justified if a LBD potential exists. However, to be effective, we contend that e.g. smart subsidies targeted to early adopters need to be offered for a limited amount of time and need to expire to aim to counter the Dixit &Pindyck delay effect. Conversely, if a limited LBD potential exists, then we contend that deployment subsidies have less justification – and that once again, it is crucial to understand the conditions under which deployment leads to learning for effective policy design, and to assess the LBD potential which will differ for each given technology. E.g. Nemet (2006) suggests that learning by doing only weakly explains changes in the most important factors influencing cost reductions in solar PV over the past 30 years, while Khanna and Chen (2014) attribute the decline in processing costs of US corn ethanol since 1983, in large part to LBD which they contend played an important role in reducing corn ethanol processing costs, exhibiting a learning rate of 0.25. Once again, the processes underlying effective R&D and learning are not completely understood. However, both are essential elements in enabling technological change and should be used to guide energy policy.

In addition, if the innovation process is a continuum, then R&D and LBD advances may exist at the same time with interactions and feedback between the two stages, in which case R&D subsidies and deployment subsidies may make sense simultaneously so as to exploit the possible interaction between the two. Once again, the technology under consideration will mostly determine how and when to allocate funds and direct policy – and evaluation of the stage of the technology and potential for LBD and R&D remains crucial.

Balancing R&D and LBD investments is a pertinent issue, with a concrete tradeoff between allocating funds in one direction of the other. We contend that optimal allocation of public resources may require a different split between R&D and deployment for different technologies, based on the estimated gains achievable through R&D efforts as well as through deployment, what kind of technology, and the stage it is in. The appropriate emphasis and sequencing of R&D and learning investments is a pertinent issue. Additionally, we question the effectiveness of a carbon tax in encouraging technology adoption at early stages of a given technology, when the technology is not commercially viable as yet. Given the high cost of the new technology, we contend that CO2 taxes would have to be very high to be effective, with the concurrent impact on political feasibility and distributional effects

3.6 Conclusion

This paper considers the question of how to transition to a meaningful percentage of renewable energy technologies in a sustainable way, and which policies are most effective in accelerating adoption. The central issue in this regard remains how best to enable technological change, and accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system. This raises the question of how best to assess the tradeoffs between alternate policy measures and crucially, how much and when to invest in which policy measure. The key question remains - what is the optimal allocation between differing policy measures, including the balance between R&D investments and downstream policy instruments across emerging renewable energy technologies?

This paper emphasizes the role of technology features in policy design, which we find is noticeably absent from most studies evaluating and comparing policy instruments in environmental policy. Most discussions evaluating policy instruments do not consider the characteristic of the technologies in question - including the stage of technology innovation, and the optimal timing and sequencing of policies in this regard, which we contend will affect the impact of differing policy instruments.

In this paper we emphasize that technology and policies must be deployed in a coordinated manner such that emission reduction benefits are achieved at an acceptable cost. We examine the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in deployment policies and LBD, and in CO2 taxes.

Based on our analysis and results we find that there is a pressing need for the reallocation of public resources from consumer subsidies towards public R&D budgets in emerging energy technologies such as solar PV, and plausibly other backstop technologies. We argue for an expanded role of aggressive R&D policies and increased public R&D funding – and contend that there is an imbalance in resources allocated towards adoption and commercialization subsidies relative to R&D investments for a technology such as solar PV that is not commercially viable. We contend that increased and aggressive R&D investments will be the key policy initiative in enabling the transition towards clean energy technologies such as solar PV in a sustainable manner.

While deployment policies and LBD are a crucial part of technical change, and they often play a key role in the large-scale uptake of new energy technologies - in general, learning is not an automatic byproduct of cumulative installed capacity, and should not be taken as such. The potential for LBD may fundamentally differ among technologies, and at different stages of a technology, and it is crucial that LBD potential is evaluate along with investments in deployment. Where deployment policies are justified, the appropriate timing and sequencing in the technology development stage is crucial. Investments in commercialization and deployment subsidies before sufficient R&D investments and breakthroughs have occurred will be ineffective and unsustainable, or alternatively will need to be very high to have any significant impact. (Torani, Rausser, and Zilberman, 2014). Widespread adoption and commercialization of emerging and unproven technologies and systems will be unlikely to occur unless sufficient major technological discoveries and improvements have taken place - which will need to be driven by appropriate and sufficient R&D investments. The logical sequence of policies necessitates first making sufficient investments and allocating resources towards R&D and the necessary technological discoveries, which can then be followed by downstream investments to enhance adoption, experience and LBD which may also feed back into the R&D process for further technological improvement and refinement (provided a LBD potential exists). In general, the appropriate emphasis and sequencing of R&D and learning investments is a pertinent issue, and optimal timing and allocation between the two depends in part on the characteristics of the technology itself.

It is in this context that we examine the effectiveness of a carbon tax in encouraging technology adoption at the early stages of an emerging renewable energy technology, while the technology is not commercially viable. While almost all economic studies find a case for imposing immediate restraints on GHG emissions, with many researchers advocating for an immediate, and at least initially low carbon tax, we find that reasonable and plausible levels of CO2 taxes may not be effective in encouraging technology adoption and reducing emissions while clean technologies are not commercially viable as yet. To be effective in encouraging technology adoption at an early stage of technological innovation, we contend that a large CO2 tax may be needed, far larger than suggested at reasonable levels – with significant implications on distributional effects and political feasibility.

We contend that the stage of technological innovation and subsequent technology readiness will determine how effective a reasonably priced carbon tax will be in encouraging clean technology adoption and emissions. With many clean technologies currently not commercially viable, a reasonably priced carbon tax may not have much of an impact on technology adoption and may not be an effective policy for reducing carbon emissions.

Once again we emphasize that technology and policies must be deployed in a coordinated manner such that the emission reduction benefits are achieved at an acceptable cost (Williams et al., 2012). Our results suggest that the first and most important stage does not lie in imposing CO2 taxes, but rather in investing in R&D and technological advancements. Once clean technologies are sufficiently ready, reasonably priced carbon taxes will bite to a larger extent and be more effective at plausible levels. Thus despite calls for immediate imposition of carbon taxes (at least at initially low levels) we contend that one plausible strategy would be either to introduce high CO2 taxes or to subsidize R&D first, followed by deployment and LBD policies, and then to impose reasonable carbon taxes – in which case scientific advances and technological changes would make CO2 emissions abatement less costly, and CO2 pricing would be effective at reasonable levels.

Crucially, this points towards the fundamental issue that R&D is a pressing and necessary part of technological innovation and our energy transition, particularly in the early stages

of emerging technologies. While deployment and LBD further comprise an important part of technological change, balancing R&D and deployment investments, and the optimal timing and allocation between the two depends on the characteristics of the technology itself. Carbon pricing is justified, however the central question in this regard remains how much and how fast to react to the threat of global warming, and at what levels carbon pricing will be effective (Nordhaus).

In general, we contend that an emphasis on technology features in policy design is crucial, since it will affect the impact and effectiveness of policy measures and will be critical in the transition towards more sustainable energy systems. The technology under consideration should in part guide and inform energy policy, as it will affect the impact and effectiveness of differing policy measures, and will determine the logical sequence and timing of policies. However we find that these considerations are noticeably absent from most studies evaluating and comparing differing policy mechanisms.

This paper illustrates the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards renewable energy technologies. We stress that optimal policies will change over time, driven primarily by the characteristics of the technology, and its stage in the innovation cycle – and that *this* will crucially determine the impact, gains and tradeoffs between alternate policy measures such as R&D policies, deployment policies, and carbon pricing policies. This analysis can be further extended by examining the role of mandates in the transition to renewable energy technologies, as well as the issues regarding introducing mandates too early when the technology isn't available. Specifically, an examination of the effects and experiences with mandates with regard to first and second generation biofuels and other emerging renewable technologies should be evaluated in further research.

Further, this analysis can be extended by a closer examination and better understanding of our current energy technology landscape and detailed technology features, including the characteristics of different technologies and their stage of development – which we contend should guide energy policy, and will affect the design of policies for differing technologies.

Lastly, future research should examine the fact that we do not yet have a clear understanding of the R&D and LBD processes, what leads to R&D and LBD gains, and how to maximize these processes and potential. There is a crucial need to pay greater attention to these issues, as well as acquiring a greater understanding of these processes and determining their potential, limitations, and gains – which is a crucial factor in informing policy design and should be addressed in future research.

Chapter 4

Managing R&D Risk in Renewable Energy: Biofuels vs. Alternate Technologies*

4.1 Introduction

Reaching the US federal government's renewable energy milestones (Table 4.1) will require efficient coordination of public and private investments. Three sets of governmental policy instruments are used to encourage private investment in renewable energy: upstream R&D investments, downstream market incentives, and downstream non-market incentives. Upstream investments in renewable energy R&D actively involve the government in the research process with the private sector. Downstream market incentives (i.e., mandates, subsidies, tax credits) are expected to lead to additional commercial developments. Downstream non-market instruments (carbon taxes) create incentives for renewable energy production by pricing externalities resulting from utilization of exhaustible resources. Each of these policy instruments is designed to alter the incentives for the use of renewable energy by making it more competitive with exhaustible sources of energy.

Historically, the economic viability of renewable energy has been determined by the prices of crude oil and natural gas. It is useful to recall Santayana's maxim "those who cannot remember the past are condemned to repeat it" when considering the rapid expansion of solar energy in the late 1970's which was brought to a halt when crude oil prices plummeted to slightly over \$10 per barrel in the mid-1980s. To eliminate this downside risk, private investors in renewable energy have actively engaged in lobbying for public funds (Rausser and Goodhue, 2002). For example, the coal industry spent millions in recent years in a lobbying effort to for a subsidization program conditioned upon crude oil prices with the following framework: if oil prices fall below \$40 per barrel, the federal government would subsidize coal based liquid fuel plants, while if oil

^{*} Co-authored with Gordon Rausser and Reid Stevens. The authors gratefully acknowledge financial support from the Energy Biosciences Institute at UC Berkeley.

prices climbed above \$80, liquefied coal companies would return a surcharge to the government.

It is unlikely that the government will be able to coordinate renewable energy investments efficiently in the face of these political economic efforts without a clear, exante investment plan. To date, the government lacks coordinated support of renewable energy technologies across upstream R&D investments and downstream (market and non-market) policy instruments. Each government agency's approach to promoting renewable energy is compartmentalized. The DOE and the USDA both use upstream R&D investments, while much of federal government legislation focuses on downstream market incentives. The problem is not unique to the US; other the major players in renewable energy (Brazil, China, and the EU) find themselves with similar uncoordinated strategies.

Without an objective, ex-ante guide for renewable energy investment, governments are likely to promote technologies based on the effectiveness of political economic efforts. This paper will provide an analysis of renewable energy technologies using portfolio analysis under risk and uncertainty. Though we restrict our analysis to the US renewable energy market, our findings are applicable to any countries that are using similar approaches to R&D investment and downstream incentives.

4.2 Current R&D Renewable Energy Landscape

R&D funding drives innovation in renewable energy. Both the federal government and the private sector are stakeholders in this process and both have an interest in successfully generating innovations that lead to enhanced productivity while decreasing damage to the environment.

4.2.1 Public Sector

The DOE's renewable energy milestones targets (Table 4.1) suggest the federal government places a positive probability on breakthroughs in renewable energy technologies. Over the past twenty years, spending on energy R&D has remained more or less constant, whereas the share of renewable energy R&D has increased over the past ten years (Figure 4.1).

Collulogia Ethonol	cellulosic ethanol cost competitive with conventional ethanol by 2012
Centriosic Ethanor	replace 30% of today's gasoline in 2030 with biofuels
Undrogon	industry commercialization possible by 2015
nyurogen	fuel cell vehicles in the showroom and hydrogen at fueling stations by 2020
Solar	reduce solar costs to grid parity in all U.S. markets by 2015
	reduce cost of energy from large systems to 3 cents\kwh by 2010
Wind	greatly expanded deployment of distributed wind energy by 2016
	large-scale offshore wind and hydrogen production from wind by 2020

Table 4.1: DOE Renewable Energy Milestones



Figure 4.1: Federal Energy R&D (\$ Millions) Source: Departmental Budget Summaries

Figure 4.2 and Table 4.2 present a more detailed breakdown of federal renewable energy R&D. Both the DOE and USDA have bioenergy R&D programs. At the DOE, spending on the biomass and biorefinery systems R&D program has been increasing steadily since 2004 in an attempt to reach the program's goal of making cellulosic ethanol cost competitive by 2012.



Figure 4.2: Federal Renewable Energy R&D, Selected Technologies (\$M) Source: IEA R&D Database

	USDA	DOE				
2002	5	92				
2003	14	86				
2004	14	69				
2005	14	89				
2006	12	90				
2007	12	150				
2008	2	198				
2009	20	214				
2010	28	220				
Source: Departmental Budget Summaries						

Table 4.2: DOE and USDA Biomass R&D (\$M)

Federal funds also support renewable energy through channels other than R&D. The Energy Independence and Security Act of 2007 amends the Renewable Fuels Standard to require 36 billion gallons of renewable fuels consumption in the U.S. by 2022, up from 9 billion gallons in 2008. The Act also authorizes \$500 million annually from 2008-2015 for the production of advanced biofuels that yield at least an 80 percent reduction in

lifecycle green-house gas (GHG) emissions (RFA, 2008a). More recently, the new Farm Bill has approved a \$1.01 per gallon credit for cellulosic biofuels, whereas the \$0.51 per gallon subsidy for conventional ethanol producers has been reduced somewhat to \$0.45 per gallon. Facilities producing energy from wind, solar, geothermal or certain types of biomass are also eligible for a 1.5 cent per kWh tax credit for the first ten years of operation. The ethanol industry also benefits from the government's ad valorem tariff of 2.5% on ethanol imports, on top of a 54 cent per gallon import charge (RFA, 2008b).

4.2.2 Private Sector

Increasing levels of public sector spending have contributed to a favorable environment for new biofuels investments and downstream incentives. Oil companies are amongst the biggest investors in biofuels. British Petroleum has stated they foresee hydrogen as the likely 'fuel of the future' (Hargreaves, 2008), even though they are also investing significant sums in cellulosic ethanol with DuPont and in public-private R&D efforts (EBI). Chevron has invested in multiple solar energy projects, a hybrid solar/fuel cell power plant, stationary fuel cell power plants and a biodiesel power plant (Chevron, 2008). Shell's renewable energy segment is investing in a global network of hydrogen refueling stations, next-generation thin-film photovoltaic cells, and an algal biodiesel demonstration project (Fortson, 2007). In mid-2009, Exxon Mobil announced a \$600 million investment in algae based biofuels with Synthetic Genomics.

Venture capital (VC) investment in renewable energy (Figure 4.3) has mirrored this exuberance. Though there was a pronounced spike in solar funding, which, at its peak, received more VC funding than all other technologies combined, funding for biofuels, solar, and wind technologies has begun to converge. In contrast, VC funding of battery, fuel cell, geothermal, and hydrogen technologies remains relatively low.



Source: Venture One Inc. Figure 4.3: Biofuels vs. Alternative Technologies VC (\$M)

4.2.3 Current Costs

Current estimated costs of renewable energy production of potential transportation fuels and electricity generation are presented in Tables 4.3 and 4.4 respectively. Costs of energy from gasoline and coal are also listed as a benchmark.

Fossil Fuel Benchmark	gasoline	0.012
Biofuels	corn ethanol	0.018
	corn stover	0.0236
	switchgrass	0.0354
	miscanthus	0.0242
	sugar cane (Brazil)	0.0101
	sugar cane bagasse	0.056
	biodiesel algae	n/a
	biodiesel waste	0.0103-0.0158
	biodiesel vegetable	
	oil	0.0159-0.0203

 Table 4.3: Renewable Energy Costs, Transportation Fuels (\$/MJ)

Fossil Fuel Benchmark	pulverized coal	0.011-0.014
Biomass	biomass electricity (no cogen)	0.014-0.019
	landfill gas electricity	0.008-0.01
	anaerobic digestion electricity	0.010-0.015
	hydrogen from wind	0.028-0.039
Other Renewable	Solar	0.083-0.11
	Wind	0.009-0.0136

Table 4.4: Renewable Energy Costs, Electricity (\$/MJ)

Table 4.3 indicates the cost of cellulosic ethanol will have to be reduced by more than half to become competitive with gasoline. However, ethanol produced from Brazilian sugar cane is already cost-competitive with gasoline, although the reported value does not include import tariffs. Electricity production from biomass is almost cost-competitive with pulverized coal, as is electricity produced from anaerobic digestion. Landfill gas electricity is already cost-competitive with pulverized coal, though this source is evidently limited in supply. Under the most favorable weather conditions, wind electricity is also cost-competitive with coal, but the variability of wind electricity costs is quite high.

4.3 Analytical Framework

The government's choice of upstream R&D investments and downstream policy instruments will determine private sector investment in renewable energy technologies. The government's policies should depend on the technology's probability distribution of cost breakthroughs for each technology and on the environmental impact. Our goal is to develop a portfolio analysis of R&D investments in renewable energy technologies through a computable portfolio model, with a Bayesian structured updating process, and generation of a time- and performance-dependent optimal mixed strategy across renewable technologies. To model the cost reduction process, we evaluate each technology in a multiple output production function framework.

4.3.1 Multiple Output Production Function Framework

Each renewable energy technology can be represented in a multiple output production function framework with two outputs: an economic output and a carbon output. The production process includes a productivity parameter with three inputs: labor, capital, and feedstock. Given the duality between production and costs, increases in the productivity parameter are equivalent to downward shifts in costs, or lower costs per MJ of energy.

This production process is consistent with the materials-balance principle, which explicitly accounts for pollution by-products as inevitable parts of the production process (Ayres and Kneese, 1969).⁵³ Life Cycle Analysis (LCA) has been used to evaluate the material balance of inputs and outputs in renewable energy production in terms of environmental emissions and marketable outputs. Though LCA has a broad scope, incorporating the total amount of extractive resources and polluting resources over the course of production, the analysis assumes coefficients are fixed rather than functions of government policies and market forces (Rajagopal and Zilberman, 2008). Until general equilibrium effects are carefully modeled, LCA will not be able to reliably estimate the net environmental impact of biofuels.

⁵³ As explained by Pethig (2006) incorporating the materials-balance principle in theoretical analyses adds significantly more computational complexity, and environmental economists have been reluctant to explicitly incorporate it in their analyses. This means much of the production processes in present models are at variance with the law of the conservation of mass; the literature has rarely produced non-linear production models that satisfy the mass balance principle (van den Bergh, 1999).

4.4 Determination of the Optimal Portfolio

Determining the optimal combination of upstream and downstream policy instruments across the technologies depends on the presumed governance structure and decision-making process. The focal decision space is the combination of policy instruments across renewable energy technologies, updated each period in accordance with a Bayesian learning model characterizing the underlying probability distributions on costs and/or productivity measures.

We acknowledge the institutional structure by explicitly modeling the private sector reaction function to government policy. The government acts as a "Stackelberg leader" maximizing its own objective function, given the private sector's reaction function, by setting a combination of upstream R&D investments and downstream market and non-market incentives. The public sector's upstream R&D investments include both basic and applied research conducted by governmental agencies, universities, and in public-private research partnerships. The public sector's downstream market incentives include price subsidization, renewable energy mandates, tax subsidies, credit subsidies, risk swaps, input subsidies, and trade distortions. The downstream non-market incentives are designed to attach prices to the production of non-market goods, like carbon, through taxes or trading schemes. Each of these policy instruments is designed to increase private sector R&D investments. The private sector reacts by investing in R&D, commercialization, and political economic efforts to maintain and expand favorable R&D investments and incentives (Rausser and Goodhue, 2002).

A governing criterion function must be specified which incorporates both the "public interest" as well as the "specialized interest" of the private sector, or more specifically the recipients of governmental transfers (Rausser et al., 2008). The maximization of this criterion function will be subject to the constraints represented by the private sector investment in R&D and commercialization as well as the portfolio of probabilistic assessments for potential technological advancements and the external forces. This formulation will allow an evaluation of vested-interest group formation which may emerge around the design and implementation of various policy instruments. Also, in the context of this formulation, the effectiveness of the design and implementation of alternative policy instruments will be assessed in terms of incidence. In the analysis reported in the paper, we focus only on the probability distributions for future technology cost reductions.

4.5 Analysis

4.5.1 Elicitation Data

A crucial first step in executing a portfolio analysis of renewable energy is an estimation of probability distributions based on elicitation from experts in each field of technology. Expert elicitation has long been used to quantify uncertainty when historical data is

unavailable by public, private, and academic research groups. Since the 1950s this approach has been used to estimate uncertain probabilities a variety of settings, from the risks posed by long-term nuclear storage to the health impacts of sulfur air pollution (EPA, 2009).

The initial step in the expert elicitation process is to identify a population of renewable energy experts working on technical/scientific breakthroughs for each technology, drawing from public, private, and academic research institutions. The experts were chosen based on citations, publications in academic journals, and participation in national laboratories or technology startups receiving venture capital funds.

	Total	University	Gov't	VC
Batteries	72	27	22	23
Biofuels	200	75	19	106
H & FC	198	87	37	74
Solar	205	108	30	67
Wind	31	9	16	6
Grand Total	706			

 Table 4.5. Expert Population

A randomly selected sub-sample of the population of experts was interviewed, with the objective of eliciting probability distributions of future costs under different funding scenarios. After each interview, we fitted distributions to the responses which were sent to the experts for feedback.

In tables 4.6-4.9 we summarize the responses for the initial round of interviews, in terms of the mean and standard deviation of the responses for the lower bound, median, and upper bound.

		,	Std.			Std.	U		Std.
Batteries	Lower	Bound Mean	dev.	M	edian Mean	dev.	Upper	Bound Mean	dev.
2 yrs Status Quo	\$	594.25	115.18	\$	618.25	79.78	\$	670.75	47.84
5 yrs Status Quo	\$	504.25	137.57	\$	556.25	105.31	\$	611.75	75.71
10 yrs Status Quo	\$	418.00	149.41	\$	472.50	140.33	\$	533.00	128.46
2 yrs Incr Funding	\$	534.25	112.51	\$	596.25	71.34	\$	638.25	51.56
5 yrs Incr Funding	\$	405.25	148.58	\$	451.00	137.95	\$	518.75	112.43
10 yr IncrFunding	\$	302.75	187.48	\$	347.25	175.01	\$	428.75	165.15
n=4									
The current specific c	ost of a 33	5kW lithium-ion	battery pa	ck is e	stimated at				
\$706/kWh									

The cost (\$/kWh) of a 35kW lithium-ion battery pack for a passenger vehicle

 Table 4.6: Batteries Data Summary

			Std.			Std.			Std.	
Fuel Cells	Lower	Bound Mean	dev.	Me	edian Mean	dev.	Upper	Bound Mean	dev.	
2 yrs Status Quo	\$	42.00	4.47	\$	47.33	5.03	\$	51.60	4.77	
5 yrs Status Quo	\$	37.40	4.34	\$	43.75	5.32	\$	49.00	7.42	
10 yrs Status Quo	\$	33.60	3.13	\$	40.25	6.29	\$	46.00	9.62	
2 yrs Incr Funding	\$	39.80	5.93	\$	44.20	5.81	\$	48.40	7.4	
5 yrs Incr Funding	\$	34.00	6.28	\$	37.40	5.98	\$	44.00	10.22	
10 yr Incr Funding	\$	26.20	9.09	\$	30.60	9.84	\$	38.60	14.74	
n=5										
The current cost (\$/kW	7) of a 80k	W direct hydrog	en PEMFO	C stack	is estimated					

The cost (\$/kW) of 80kW direct hydrogen PEM fuel cell stack for transportation applications

Table 4.7: Fuel Cells Data Summary

The cost (\$/kWh) of commercial scale PV Solar electricity generation	The cost (S	(\$/kWh) of co	mmercial scale	e PV Solar	electricity	generation.
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		Std.			Std.			Std.	
Solar	Lower Bound Mean	Dev.	Me	edian Mean	Dev.	Upper	Bound Mean	Dev.	
2 yrs Status Quo	\$ 0.12	0.028	\$	0.16	0.021	\$	0.18	0.035	
5 yrs Status Quo	\$ 0.09	0.014	\$	0.12	0.004	\$	0.15	0	
10 yrs Status Quo	\$ 0.07	0.014	\$	0.10	0.028	\$	0.13	0.035	
2 yrs Incr Funding	\$ 0.11	0.035	\$	0.14	0.028	\$	0.17	0.028	
5 yrs Incr Funding	\$ 0.08	0.007	\$	0.11	0.004	\$	0.15	0.007	
10 yr Incr Funding	\$ 0.06	0.007	\$	0.09	0.007	\$	0.11	0.014	
n=2									
The current cost of co	mmercial scale PV Sola	r electricity g	generati	ion is					
\$0.18/kWh.									

Table 4.8: Solar Data Summary

The cost (\$/kWh) of biofuels from the biochemical conversion of cellulosic biomass.

			Std.			Std.			Std.
Biofuels	Lower Bound Mean		dev.	Me	edian Mean	dev.	Upper	Bound Mean	dev.
2 yrs Status Quo	\$	0.10	0.014	\$	0.12	0.009	\$	0.18	0
5 yrs Status Quo	\$	0.07	0	\$	0.11	0.000	\$	0.14	0
10 yrs Status Quo	\$	0.05	0.007	\$	0.09	0.003	\$	0.11	0
2 yrs Incr Funding	\$	0.10	0.007	\$	0.11	0.009	\$	0.15	0.024
5 yrs Incr Funding	\$	0.06	0	\$	0.10	0.005	\$	0.12	0
10 yr Incr Funding	\$	0.05	0.006	\$	0.08	0.008	\$	0.10	0.008

n=2

at \$50/kW.

The current cost per gallon (\$/gallon) of biofuels from biological conversion of cellulosic biomass is estimated to be between \$2.95-\$4 per gallon.

The energy content of biofuels is estimated as assume 75,700 btu per allon.

Table 4.9: Biofuel Data Summary

As expected, these preliminary results reveal a significant impact on cost reductions resulting from the hypothetical funding increase. An increase in funding is associated with a 16% decrease in the expected cost of batteries, a 13% decrease in the expected cost of fuel cells, a 10% decrease in the expected costs of solar cells, and a 10% decrease in the expected cost of biofuels. A funding increase also significantly decreases the expected variance of future cost reductions.

Though the current results indicate that the probability distribution of biofuels nearly stochastically dominates the other renewable energy technologies (with some overlap to be observed with solar PV technologies), we anticipate that further interviews will yield more concrete results and display an increase in the overlap between distributions which will allow for rigorous portfolio analysis.

The subsequent portfolio analysis is designed to allocate R&D investments across renewable energy technologies in a manner that minimizes the risk for a specified level of expected returns, taking into account both the expected reductions in cost and the variance of the expectations of cost reductions, and thus providing an objective benchmark for efficient allocation of resources across renewable energy technologies.

4.6 Conclusion

Currently there is no clear, *ex ante* plan to guide upstream or downstream public support of renewable energy technologies. As a result, it will be difficult for the public sector to avoid the pull of special interests working to obtain insurance against the downside risks of clean energy investments made by private firms, and to avoid the pitfalls of industrialization policies. It is with this motivation that we have outlined an analytical framework to determine the optimal combination of upstream R&D investments and downstream instruments. Our framework is based on the estimation of probability distributions for potential future cost reductions resulting from R&D investments from the public and private sectors.

Our early stage results reveal that a hypothetical increase in total R&D funding has a significant impact on cost reductions, as well as a decrease in the variance of the probability distributions. Though biofuels show the most promise among the initial probability distributions, we anticipate further interviews to reveal an increase in the overlap among the technology future cost probability distributions. We anticipate that the portfolio analysis can guide the public sector as it invests amongst the numerous renewable energy technologies. Such an ex-ante guide is essential if the public sector is to achieve an efficient allocation of renewable energy public R&D investment in combination with downstream policy instruments across the emerging technologies. The challenge for governments is to exploit the complementarities between upstream R&D investments and downstream market and non-market incentives.

Chapter 5

Conclusions

This dissertation presents both a theoretical and empirical examination of the optimal allocation of public R&D investments in combination with downstream policy instruments across emerging renewable energy technologies. We consider the question of how best to enable technological change, accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system. We examine the question of how best to assess the tradeoffs between alternate policy measures, which policies are most effective in accelerating adoption, and crucially, how much and when to invest in which policy measure. The key question remains - what is the optimal allocation between differing policy measures, including the balance between R&D investments and downstream policy instruments across emerging renewable energy technologies?

In the first essay, chapter 2, we consider the question of how to transition to a meaningful percentage of solar energy in a sustainable manner and which policies are most effective in accelerating adoption. We develop a stochastic dynamic real options model of the adoption of solar PV in the residential and commercial sector, evaluating the threshold and timing of the consumer's optimal investment decision given two sources of uncertainty. We simulate the model to obtain a cumulative likelihood and timing of substitution amongst energy resources and towards solar under plausible rates of technological change, electricity prices, subsidies and carbon taxes.

The results indicate that there will be a displacement of incumbent technologies and a widespread shift towards solar PV in the residential and commercial sector in under 30 years, under plausible parameter assumptions - and that crucially, this can occur independent of consumer subsidies and carbon pricing policies (at \$21/ton CO2, \$65/ton CO2 and \$150/ton CO2). In general, results across all scenarios consistently indicate that average historic consumer subsidies and carbon pricing policies have a modest effect in accelerating adoption, and may not be an effective part of climate policy in this regard.

Instead, the results demonstrate that R&D support and further technological change is the crucial determinant and main driver of widespread adoption of solar PV - suggesting that subsidies and taxes don't make a substantial difference in a technology that's not viable, while research does. This further suggests that optimal policies may change over time, however current continued R&D support and technological advancement is the crucial determinant of widespread transition to solar and plausibly other backstop technologies – and that it should play a key role in policy measures intended to combat climate change. Further, results indicate that subsidies and taxes become increasingly ineffective with higher rates of technological change.

The results do not imply that carbon pricing shouldn't play a role in climate policy in general. Carbon pricing may be effective in reducing emissions and encouraging the transition towards other clean technologies – however it has a decidedly modest impact in accelerating adoption of solar PV at levels up to \$150/ton CO2. Suggesting, that if a widespread transition to solar energy is likely to happen in this sector, it will be because of R&D and technological advancement.

The final sections of this dissertation examine the role of technology features in policy design. We illustrate the key role of the technology innovation cycle and changing optimal policies at every stage of the technology in the transition towards renewable energy technologies. We stress that optimal policies will change over time, driven primarily by the characteristics of the technology, and its stage in the innovation cycle – and that *this* will crucially determine the impact, gains and tradeoffs between alternate policy measures such as R&D policies, deployment policies, and carbon pricing policies.

We consider the characteristics of the technologies in question, including the stage of technology innovation, and the optimal timing and sequencing of policies in this regard - which we find will affect the impact of differing policy instruments, and which is noticeably absent from most studies evaluating and comparing policy instruments in environmental policy.

We emphasize that technology and policies must be deployed in a coordinated manner such that emission reduction benefits are achieved at an acceptable cost. We examine the stages of the technology innovation process and the role of policy incentives at every stage - including the timing, sequencing, and role of investments in public R&D, in deployment policies and LBD, and in CO2 taxes.

Based on our analysis and results we find that there is a pressing need for the reallocation of public resources from consumer subsidies towards public R&D budgets in emerging energy technologies such as solar PV, and plausibly other backstop technologies. We argue for an expanded role of aggressive R&D policies and increased public R&D funding – and contend that there is an imbalance in resources allocated towards adoption and commercialization subsidies relative to R&D investments for a technology such as solar PV that is not commercially viable. We contend that increased and aggressive R&D investments will be the key policy initiative in enabling the transition towards clean energy technologies such as solar PV in a sustainable manner.

While deployment policies and LBD are a crucial part of technical change, and they often play a key role in the large-scale uptake of new energy technologies - in general, learning is not an automatic byproduct of cumulative installed capacity, and should not be taken as such. The potential for LBD may fundamentally differ among technologies, and at different stages of a technology, and it is crucial that LBD potential is evaluated along with investments in deployment.

Where deployment policies are justified, the appropriate timing and sequencing in the technology development stage is crucial. Investments in commercialization and

deployment subsidies before sufficient R&D investments and breakthroughs have occurred will be ineffective and unsustainable, or alternatively will need to be very high to have any significant impact (Torani, Rausser, and Zilberman, 2014). Widespread adoption and commercialization of emerging and unproven technologies and systems will be unlikely unless sufficient major technological discoveries and improvements have taken place - which will need to be driven by appropriate and sufficient R&D investments. The logical sequence of policies necessitates first making sufficient investments and allocating resources towards R&D and the necessary technological discoveries, which can then be followed by downstream investments to enhance adoption, experience and LBD. In general, we find that the appropriate emphasis and sequencing of R&D and learning investments is a pertinent issue, and optimal timing and allocation between the two depends in part on the characteristics of the technology itself.

We further examine the effectiveness of a carbon tax in encouraging technology adoption at the early stages of an emerging renewable energy technology, while the technology is not commercially viable. While almost all economic studies find a case for imposing immediate restraints on GHG emissions, with many researchers advocating for an immediate, and at least initially low carbon tax, we find that reasonable and plausible levels of CO2 taxes may not be effective in encouraging technology adoption and reducing emissions while clean technologies are not commercially viable as yet. To be effective in encouraging technology adoption at an early stage of technological innovation, we contend that a large CO2 tax may be needed, far larger than suggested at reasonable levels – with significant implications on distributional effects and political feasibility. We find that the stage of technological innovation and subsequent technology readiness will determine how effective a reasonably priced carbon tax will be in encouraging clean technology adoption and emissions.

Once again we emphasize that technology and policies must be deployed in a coordinated manner such that the emission reduction benefits are achieved at an acceptable cost (Williams et al., 2012). Our results suggest that the first and most important stage does not lie in imposing CO2 taxes, but rather in investing in R&D and technological advancements. Once clean technologies are sufficiently ready, reasonably priced carbon taxes will bite to a larger extent and be more effective at plausible levels. Thus despite calls for immediate imposition of carbon taxes (at least at initially low levels) we contend that one plausible strategy would be either to introduce high CO2 taxes or to subsidize R&D first, followed by deployment and LBD policies, and then to impose reasonable carbon taxes – in which case scientific advances and technological changes would make CO2 emissions abatement less costly, and CO2 pricing would be effective at reasonable levels.

In general, we find that an emphasis on technology features in policy design is crucial, since it will affect the impact and effectiveness of policy measures and will be critical in the transition towards more sustainable energy systems. The technology under consideration should in part guide and inform energy policy, however we find that these considerations are noticeably absent from most studies evaluating and comparing differing policy mechanisms.

In this dissertation, all three chapters consider the question of how to enable technological change, accelerate innovation and widespread adoption of new energy technologies and move towards a more sustainable energy system. All three papers raise one key question - what is the optimal allocation between differing policy measures, including the balance between R&D investments and downstream policy instruments across emerging renewable energy technologies? In its entirety, this dissertation considers which policies are most effective in accelerating adoption, and crucially, how much and when to invest in which policy measure – with a special emphasis on the importance of understanding innovation and technology features in policy design.

It is in this context that there are several issues that should be addressed in future research. Most importantly, a closer examination of the technology landscape and particular technology features is crucial. A deeper and more detailed examination of technologies such as solar PV illustrates that the main cost drivers consist of both equipment and installation – which will affect the LBD potential in both these areas, and subsequently the justification for subsidies will be driven by both these factors. A closer examination of how much of the existing subsidies were devoted to each of these areas (installation versus new equipment), as well as the potential for cost reductions in both these areas is pertinent - and innovation and policy may affect these two elements differently. In general, a more refined consideration of technologies and their cost drivers, supply chain issues, and infrastructure requirements will be crucial in developing a deeper understanding of innovation, and policy design and impact. Ultimately, different technologies will require a different structure of investment based on their particular characteristics and features.

In addition, future research should deconstruct and examine the innovation process in more detail. It is also crucial to attempt to learn from the high rates of innovation displayed in other areas such as high tech and biotech. It is extremely important to examine questions regarding who conducts research, public and private issues, the role of universities versus companies, and issues of technology transfer - in particular with regard to the field of renewable energy technologies. These considerations should be addressed in future research in an attempt to deepen our understanding of the innovation process, technological change and appropriate policy design.

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APPENDIX A

Overall, the results of the simulations for electricity price parameters based on EIA historical average residential and commercial electricity prices of -0.2479% and 0.2011% (for the time periods 1990-2002 and 2003-2009 respectively) indicate the following: (i) As expected, a low or negative evolution of the price of electricity delays adoption considerably. (ii) Both consumer subsidies and carbon taxes display a modest increase in impact with lower growth rates of electricity prices. (iii) However, results remain consistent across all scenarios of differing electricity price trajectories with overall results demonstrating that further technological change is the crucial determinant and main driver of adoption.

PELEC -0.248%						
		BASELINE			NSUMER INC	ENTIVES
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	21y	19y 6m	15y 6m	16y 7m	15y 8m	13y 2m
40%	44y 10m	36y 3m	24y 9m	34y 5m	30y 9m	22y
50%	54y 2m	42y 9m	27y 8m	40y 1m	36y 11m	25y 1m
60%	66y	47y 10m	31y 1m	53y 10m	44y 4m	28y
70%	84y 10m	59y 11m	34y 11m	69y	60y 1m	31y 10m
80%	Not within 90 years	87y 5m	40y 5m	Not within 90 years	79y 2m	37y 1m
90%	Not within 90 years	Not within 90 years	Not within 90 years	Not within 90 years	Not within 90 years) 56y 8m

Table A.1 – Baseline Results for Likelihood and Timing of Adoption & Impact of Average Historic Consumer Incentives (pelec = -0.248%, r=3%)

PELEC +0.2011%		BASELINE			AV. CONSUMER INCENTIVES		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	
10%	19y 3m	18y 3m	15y 1m	15y 3m	14y 7m	13y 1m	
40%	38y 8m	33y 8m	23y 7m	32y 4m	27y 7m	20y 9m	
50%	48y 5m	39y 4m	26y	38y 8m	32y 4m	23y 4m	
60%	58y 2m	46y 2m	29y 2m	50y 11m	39y 9m	26y 2m	
70%	85y 7m	55y	32y 10m	67y 6m	46y 11m	29y 9m	
80%	Not within 90 years	67y 2m	38y 11m	Not within 90 years	68y 8m	34y 3m	
90%	Not within 90 years	Not within 90 years	54y 10m	Not within 90 years	Not within 90 years	53y 3m	

Table A.2 – Baseline Results for Likelihood and Timing of Adoption & Impact of Average Historic Consumer Incentives (pelec = +0.2011%, r=3%)

*Base Case*⁵⁴: Results for the cumulative likelihood and timing of adoption for the average consumer are shown in tables A.1 and A.2 across alternative R&D and technological advancement scenarios in solar. Table A.1 shows results for annual electricity price growth rates of -0.2479%, while table A.2 shows the results for annual electricity price growth rates of +0.2011% as based on EIA historic average residential and commercial electricity prices.

Projections for annual electricity price growth rates of -0.2479% indicate that independent of any incentives or carbon pricing, if historic lower technological change rates are maintained, there is a 50% likelihood of adoption within approx. 54 years, and a 60% likelihood within approx. 66 years. However, if the higher average cost declines observed within the recent years are maintained, it would accelerate adoption considerably, resulting in a 50% likelihood of adoption within 28 years, and a 60% likelihood within 31 years. In this latter scenario, under an entirely plausible rate of technological change, and with negative growth in electricity prices, projections indicate that there could be a widespread shift towards solar in under 30 years in the residential and commercial sector – without any incentives or carbon pricing.

⁵⁴ We present the simulation results for r = 3%. However, consistent with the analytical results which illustrate the relative insensitivity of ROA to interest rate changes, the simulation results are very similar across r = 3% and 5%, exhibiting the same key dynamics. In addition, we discuss results at the 50-60% likelihood level.

These results are similar to those for annual electricity price growth rates of +0.2011%, which indicate that independent of any incentives or carbon pricing, if historic lower technological change rates are maintained, there is a 50% likelihood of adoption within approx. 48 years, and a 60% likelihood within approx. 58 years. If the higher average cost declines observed within the recent years are maintained, in this scenario, it would accelerate adoption considerably, resulting in a 50% likelihood of adoption within 26 years, and a 60% likelihood within 29 years. Again, in this scenario, under an entirely plausible rate of technological change, projections indicate that there could be a widespread shift towards solar in under 30 years in the residential and commercial sector – without any incentives or carbon pricing. Additionally, as expected, higher growth rates in electricity prices accelerate adoption in general as compared to the previous scenario with negative growth in electricity prices.

Average Historic Consumer Incentives: Recent cost declines in solar PV have been accompanied with declining consumer incentives across most states - which many fear will dampen the overall consumer economics of solar adoption. Consistent with the results for annual electricity price growth rate of +2.89%, our results strongly suggest that these concerns are overstated, even in the scenario with lower annual growth rates of electricity prices of -0.2479% and 0.2011%.

Results for annual electricity price growth rates of -0.2479% (table A.1) indicate that if recent rates of cost decline are maintained, average historic consumer incentives will have a minimal impact of accelerating adoption by approximately 3 years as compared to the base case scenario. This is consistent with results for both electricity price growth rates of +0.2011% (table A.2) and +2.89% (table 2.8).

In the scenario with the lower historic rate of technological advancement, projections indicate a slightly higher impact of consumer incentives, accelerating adoption by an approximately 13 years (versus 8 years and 5-6 years for the scenarios with electricity price growth rates of +0.2011% and +2.89% respectively) as compared to the base case, albeit with widespread adoption occurring only within 47 years.

In general, the results indicate a difference of 3-13 years depending on cost decline scenarios (versus 3-8 years and 3-6 years for the scenarios with electricity price growth rates of +0.2011% and +2.89% respectively), strongly suggesting the policy conclusion that in general, average historic incentives have a modest impact in encouraging adoption of solar technologies, and virtually no impact if the recent higher cost declines are maintained. The impact does however show a relative increase in scenarios with lower technological change and declining electricity price rates.

PELEC -0.248% CO2 Tax (\$21/ton CO2)		COAL			NATURAL GAS		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	
10%	17y 5m	16y 9m	14y 2m	19y 3m	18y	14y 10m	
40%	37y 10m	33y 1m	22y 4m	42y 10m	33y 11m	23y 10m	
50%	47y 5m	39y 3m	24y 10m	53y 2m	39y 5m	26y 11m	
60%	59y 1m	46y 7m	28y	64y 4m	48y 7m	29y 8m	
70%	74y 8m	59y 11m	32y 4m	Not within 90 years	58y 4m	33y 4m	
80%	Not within 90 years	87y 6m	38y 2m	Not within 90 years	Not within 90 years	n 38y 10m	
90%	Not within 90 years	Not within 90 years	61y 2m	Not within 90 years	Not within 90 years	n 52y 2m	

Table A.3 – Impact of \$21/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = -0.248%, r=3%)

Table A.4 – Impact of \$21/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = +0.2011%, r=3%)

PELEC +0.2011%	COAL			NATURAL GAS		
CO2 Tax (\$21/ton CO2)						
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	16y 4m	15y 7m	13y 7m	17y 5m	16y 8m	13y 11m
40%	33y 4m	29y 10m	21y 10m	36y 8m	31y 2m	21y 2m
50%	41y 3m	34y 1m	24y 8m	47y	37y 4m	24y 5m
60%	52y 3m	40y 8m	27y 6m	56y 9m	43y 3m	27y 4m
70%	64y 9m	46y 9m	32y 3m	72y	51y 11m	31y 6m
80%	Not within 90 years	68y 11m	37y 9m	Not within 90 years	69y 9m	36y 2m
90%	Not within 90 years	Not within 90 years	Not within 90 years	Not within 90 years	Not within 90 years	52y 10m

Carbon Taxes At \$21/ton CO2 and \$65/ton CO2: Results for a carbon tax of \$21/ton CO2 and \$65/ton CO2, representing SCC estimates for "most likely" and "higher-than expected" impact scenarios are shown in tables A.3 - A.6 respectively. Projections for annual electricity price growth rates of -0.2479% indicate that a \$21/ton CO2 carbon tax accelerates adoption by an average of 1 - 7 years, with a consistently lower impact in the scenario with the higher rate of technological advancement (table A.3). This result is only slightly higher that the results for both electricity price growth rates of +0.2011% (1-6.5 years) and +2.89% (0-3 years) as shown in tables A.4 and 2.9 respectively.

For electricity price growth rates of -0.2479%, the carbon tax would accelerate adoption by 1-1.5 years if the source of electricity were derived from natural gas, and by 3-7 years if derived from coal. Projections strongly suggest that while this may be the most feasible level of carbon pricing, it is also the most ineffective and has a modest impact in accelerating adoption across all growth rates for the price of electricity. Notwithstanding growth and distributional effects - a carbon tax of \$21/ton CO2 would raise the price of a gallon of gasoline by \$0.19 and a barrel of crude oil by \$9.03.

Projections for annual electricity price growth rates of -0.2479% indicate that a \$65/ton CO2 carbon tax accelerates adoption by an average of 3-9 years (table A.5), once again with a consistently lower impact in the scenario with the higher rate of technological advancement. These results are again only slightly higher that the results for both electricity price growth rates of +0.2011% (3.5-6.5 years) and +2.89% (2-5 years) as shown in tables A.6 and 2.10 respectively.

Specifically, if the recent average cost declines in solar are maintained, results indicate an average of 3 years difference if derived from natural gas and 6 years difference if derived from coal.

Only in the scenario with historical lower rates of technological advancement and coal as the incumbent source of electricity will the tax have a more significant impact of accelerating adoption by an average of 12.5 years – however projections still indicate that widespread adoption will occur on average in almost 47.5 years in this scenario with 50-60% likelihood. This result is slightly higher that the results for this scenario for both electricity price growth rates of +0.2011% (11 years) and +2.89% (8 years) as shown in tables A.6 and 2.10 respectively.

PELEC -0.248% CO2 Tax (\$65/ton CO2)		COAL		N.	ATURAL GA	GAS	
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	
10%	14y 9m	14y 8m	11y 8m	17y 4m	15y 6m	13y 7m	
40%	34y 3m	28y 6m	19y /m	36y 5m	30y 4m	21y 11m	
50%	42y 10m	34y	21y 11m	44y 10m	3/y 3m	24y 9m	
60%	52y	41y 1m	24y 11m	57y 5m	45y 5m	27y 9m	
70%	69y 8m	50y 1m	28y 6m	71y 6m	61y 10m	31y 7m	
80%	Not within 90 years	65y 5m	33y 3m	Not within 90 years	Not within 90 years	37y 5m	
90%	Not within 90 years	Not within 90 years	42y	Not within 90 years	Not within 90 years	52y 5m	

Table A.5 – Impact of 65/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = -0.248%, r=3%)

Table A.6 – Impact of \$65/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = +0.2011%, r=3%)

PELEC +0.2011% CO2 Tax (\$65/ton CO2)	COAL			NATURAL GAS		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	13y 6m	12y 7m	11y 9m	16y	15y 4m	12y 6m
40%	30y 4m	25y	18y 10m	34y 3m	28y 11m	20y 1m
50%	36y 6m	29y 4m	21y 4m	41y 11m	34y	22y 7m
60%	47y 5m	36y 5m	24y 2m	50y 8m	40y 11m	25y 5m
70%	63y 9m	45y 2m	27y 7m	63y 10m	49y 7m	28y 9m
80%	Not within 90 years	69y 9m	32y 10m	Not within 90 years	63y 11m	33y 7m
90%	Not within 90 years	Not within 90 years	42y 11m	Not within 90 years	Not within 90 years	42y 9m

Concurrently, a carbon tax of \$65/ton CO2 would raise the price of a gallon of gasoline by \$0.58, and a barrel of crude oil by \$27.95.

Carbon Taxes At \$150/ton CO2: While a carbon tax of \$150/ton CO2 has not been included in government estimates of the social cost of carbon (SCC), it has been suggested as representing considerations of catastrophic climate outcomes more accurately than lower estimates (Pindyck 2013).

The results for the impact of a carbon tax of 150/ton CO2 with electricity growth rates - 0.2479% are shown in table A.7, while results for electricity growth rates of +0.2011% are shown in table A.8.

Projections for annual electricity price growth rates of -0.2479% indicate that if recent rates of cost decline are maintained, the carbon tax would accelerate adoption by a modest 6-10 years above baseline results free of any incentives. This result is only slightly higher than the results for this scenario for both electricity price growth rates of +0.2011% (6-8.5 years) and +2.89% (6-8 years) as shown in tables A.8 and 2.11 respectively.

PELEC -0.248% CO2 Tax (\$150/ton CO2)	COAL			NATURAL GAS		
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	9y 9m	9y 5m	9y 2m	14y 5m	13y 1m	11y 2m
40%	25y 10m	21y 2m	15y 5m	32y 3m	26y /m	18y 10m
50%	32y 11m	24y 9m	18y	40y	31y/m	21y /m
60%	41y	31y 1m	20y 7m	49y 7m	38y 6m	24y 8m
70%	58y 3m	37y 10m	23y 9m	69y 10m	49y 2m	28y 4m
80%	90y	58y	28y 2m	Not within 90 years	68y 4m	34y 3m
90%	Not within 90 years	Not within 90 years	40y 4m	Not within 90 years	Not within 90 years	51y 10m

Table A.7 – Impact of \$150/ton CO2 Tax on Likelihood and Timing of Adoption (pelec = -0.248%, r=3%)

PELEC +0.2011% CO2 Tax (\$150/ton CO2)	_	COAL			TURAL GAS	5
Likelihood of Adoption	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)	Historic lower tech advancement (-4.4%)	50% Increase in R&D funding (-5.6 %)	Recent higher Av. Cost Decline (-9.3%)
10%	9y 5m	9y 5m 20y 1m	9y 1m	12y 4m 28y 7m	11y 10m	10y 7m
40% 50%	22y 10111 27y 7m	20y 111 24y 4m	13y 411 17y 6m	28y 7111 34y 7m	25y 8iii 27y 6m	1/y 4111 19y 10m
60%	34y 7m	24y 411 28y 11m	20y 3m	44y 3m	32v 10m	22v 6m
70%	45y	37y 5m	23y 6m	57y 6m	41y 1m	25y 8m
80%	74y 1m	50y 5m	27y 10m	89y 3m	57y 5m	30y 1m
90%	Not within 90 years	Not within 90 years	35y 11m	Not within 90 years	Not within 90 years	44y 2m

Table A.8 - Impact of \$150/ton CO2 Tax on Likelihood and	Timing of Adoption
(pelec = +0.2011%, r=3%)	

The impact is more significant in the scenario with historical lower rates of technological advancement – accelerating adoption by an average of 15 and 23 years, given the incumbent source of electricity is derived from natural gas and coal respectively. These results are again only slightly higher than projections for the scenarios with electricity price growth rates of +0.2011% (13.5 and 21.5 years respectively) and +2.89% (10 and 15.5 years respectively) as shown in tables A.8 and 2.11 respectively.

However, projections indicate that a tax of \$150/ton CO2 applied to the lower technical change scenario (for both electricity derived from coal and natural gas) will still <u>not</u> replicate the baseline results for the higher rates of technical change free of any incentives – a higher carbon tax than \$150/ton CO2 would be necessary to do so. In general, this result holds for all three electricity price growth rate scenarios (i.e. -0.2479%, +0.2011% and +2.89%)⁵⁵.

Concurrently, a \$150 carbon tax would raise the price of a gallon of gasoline by \$1.33, and the price of a barrel of crude by approx. \$65. In addition, a \$150 tax would more than double the current price of electricity (if derived from coal), rendering it almost as high as the current cost of solar free of incentives.

⁵⁵ With the exception of the case with electricity price growth at +2.89%, the lower technical change scenario and the incumbent source of electricity derived from coal - in which case a tax of 150/ton CO2 will replicate baseline results for the higher rate of technical change free of any incentives.