An Agent-based Model of Technological Lock-in

by

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An essay submitted to the Department of Economics in partial fulfillment of the requirements for the degree of Master of Arts

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Acknowledgements

I would like to thank Professor Robin Boadway for his guidance and insight as my professor and advisor, my family for their encouragement, and the MA class of 2012 for their support.

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Chapter 1

Introduction

Climate change is widely regarded as one of the most formidable challenges facing society. While few now question the need to reduce carbon dioxide emissions, debate rages on the most cost effective way to do so, on who should bear the burden, and whether immediate action should be taken. With society caught between the benefits of our modern energy intensive lifestyles and the impact of the resulting greenhouse gas emissions, the need for alternative energy sources has become clear.

Shifting away from fossil fuels entails a number of significant challenges, the principal one of which is the high cost of alternative energy. In the current absence of widespread willingness to bear higher costs for clean energy, and the developing world's surging demand for energy of any form, technological innovation to obtain low cost and clean energy is an important goal.

General technological change has received extensive coverage in the economics literature. Work has examined the processes of invention and diffusion of technologies, [Silverberg and Dosi. . . , 1988] how knowledge spillovers transfer information and improvements between agents involved in innovation,[Clarke et al., 2006] the role of firms and government,[Clarke et al., 2008] whether research is private or publicly funded and the different social and private rates of return.[Mansfield, 1996] The effects of patents and policy structures, basic vs applied research, and the process of learning-by-doing have all been studied.[Clarke et al., 2006, Clarke et al., 2008, Sandén and Azar, 2005]

Technological innovation has also been the focus of research through economic models important for environmental policies.[Löschel, 2002, Popp, 2006b] To understand the interaction of the economy and global warming, a variety of computational models have been developed. Models are usually one of two forms, bottom-up or top-down. Bottom-up models focus on energy systems, are typically engineering-focused, and may treat economic and climate effects as exogenous.[Grübler and Gritsevskii, 1997] Top-down models focus on macroeconomic effects, and integrate in climate and energy components. These "integrated assessment models" have been influential in producing estimates of emissions targets and policy analysis.[Nordhaus. . . , 1999] IAM's generally include a macroeconomic model of the economy including emissions from energy use, and a climate feedback that translates these emissions into estimated economic damages via global warming. The long time frame of climate change damages and policies, on the order of decades, means that technological change is a vital component in both bottom-up and top-down models.

The first IAM models included technological change as an exogenous effect, such as via a decrease in the energy intensity of aggregate production. The process of innovation is clearly not exogenous, and endogenizing technological change has been the focus of recent research.[Popp, 2006a, Popp, 2004] That innovation is dependent on energy prices is not conjecture. Popp used patent data to show how energy prices strongly impact innovation rates,[Popp, 2001] while Newell et al showed that the efficiency of air conditioners rose in response to oil price hikes.[Newell and Jaffe. . . , 1999] However even endogenous models of technological change treat the process of innovation as a deterministic one, albeit with perhaps uncertain parameters. It has been recognized that such an approach poorly captures the complex dynamics of innovation.[Grübler and Gritsevskii, 1997, Pizer and Popp, 2008]

The invention of new technologies is not a purely Schumpeterian creative destruction process, where the most superior technology wins in a marketplace of ideas. As new technologies are developed, seemingly minor events early on can have large effects on the evolution and adoption of the technology. This quality of being dependent on history and initial conditions, and not exclusively on a technology's merit, is path-dependency.[Unruh, 2000, David, 2001] The Betamax and VHS format war is likely the most famous example, where the supposedly superior Betamax lost to VHS, which came to dominate the market. With the same technology, but perhaps slightly different historical influences, perhaps Betamax would have become the dominate technology. Path dependency can occur for a variety of reasons. Adoption may be a chaotic process with potentially high sensitivity to initial conditions, such as initial marketing efforts. Small network effects may give one technology an initial advantage, leading to its widespread adoption and the exclusion of a competitor. Related to this is technological lock-in, where an existing technology has sufficient advantages that it is able to keep out or delay the adoption of a competitor.[Kline, 2001] Which technology is locked-in is often path-dependent, as in the example of VHS.

While not always symptomatic of a market failure, there is a form of path dependency and lock-in that is. Technologies tend to become cheaper through repeated production, as in learning-by-doing. This improvement due to deployment and use gives an established technology a cost advantage over newcomers to the market, further encouraging deployment of the established technology. A cycle of increased use due to a lower cost, further improvements, and decreasing costs, can continue until there is an insufficient incentive to deploy a more expensive technology. A market failure develops if this path dependency and lock-in combine to prevent superior technologies from being adopted, technologies which would be beneficial in the long run.

An example of this is pressurized water reactors, (PWRs) the worldwide dominant model of nuclear power plant. The first civilian nuclear reactor was a PWR, and early research into the design was favoured due to its easy miniaturization for nuclear submarines. The experience gained led to subsequent PWR power plants, and little incentive to fund research into additional designs. Unfortunately it is believed that this design is inferior to others in cost and safety, but other designs have been unable to attract sufficient investment and experience to become economically competitive. As a result, we have been locked into a potentially more expensive and unsafe technology.[Cowan, 1990]

The problem of path dependency and lock-in has been studied for some time, since pioneering work by Arthur.[Arthur, 1989] Several simple models of technological lock-in have been developed.[Arthur, 1989, Kalkuhl et al., 2012, Dolfsma and Leydesdorff, 2009, Cowan, 1991, Sood and Tellis, 2005, Gritsevskyi and Ermoliev, 2012, Islas, 1997] Arthur discussed how historical events and path dependency such as 'unexpected successes in the performance of prototypes' can lead to lock-in, and focused on the role of increasing, decreasing, and constant returns to scale. The model used agents choosing between two technologies based on their preferences and the number of previous adopters, showing how lock-in can occur under increasing returns, but not constant or decreasing returns. The author recognizes that this can lead to technologies which are established early, but are not ultimately superior, becoming locked-in. Sood discusses the performance of a technology over time, and surveys technologies to demonstrate that their improvement comes in an irregular staircase like manner. Cowan extends this to argue that even with a central planner, the uncertainty of a technology's development can result in lock-in to an inferior technology. This is similar to the two armed bandit problem, where one must choose between two options with different payoffs, but gain information about the payoffs through repeated sampling. Dolfsma expands on these models to consider how breakout from lock-in is possible.

Gritsevskyi and Ermoliev recognize the importance of path dependency and lock-in in IAM models. They discuss the challenges of endogenizing technological change, and illustrate lock-in and path dependency through a "urn's scheme" model. Importantly, they discuss technological change in the context of experience curves, but do not use them for modelling.

Kalkuhl et al are the first to include lock-in of energy technologies within a simplified integrated assessment model, an inter-temporal general equilibrium model, and consider the implications of this. Their paper considers the effects of lock-in to inferior technologies, and the welfare losses this causes. Several policy interventions are explored, with the goal of maximizing welfare through reducing the negative impact of lock-in. These policies are: subsidies for carbon-free technology, quotas for different technologies, feed-in-tariffs, taxes on the mature carbon-free technology, and carbon pricing. Technological change is included through learning-by-doing from increased deployment, which increases a carbon-free technology's productivity.

The authors note the importance of niche markets and the substitutability between technologies in maintaining demand for the learning technology in order for it to "gain experience and reduce production costs until it becomes competitive." Policies designed to encourage adoption of alternative energy are analyzed by comparing consumption losses. Their deterministic model shows only small differences between subsidies, feed-in-tariffs, and technology-specific quotas. The policies considered are optimal, and the paper considers the implications of non-optimal policies by varying them by 1% from the optimum.

They find that in general the policies are not sensitive to this change, with the exception that a subsidy set too low can cause significant consumption losses. They attribute this to lock-in, where the subsidy is unable to make the new technology sufficiently competitive to break the existing lock-in. As the model assumes perfect knowledge of the new technologies' potential for improvement, the authors compare their results to a case where the government implements policies based on an incorrect assessment of a technology's potential. The policies are still successful in reducing consumption losses, "hence imperfect information is no argument for non-action."

Kalkuhl et al show the importance of policy, and the dangers of lock-in, recognizing how the substitutability of electricity makes lock-in more of a risk. However they have not examined the complexity of innovation and of lock-in itself, and their model does not capture how different polices can affect the course of innovation. Without a detailed consideration and illustration of technological lock-in and path dependency, its importance in modelling and in setting policy to encourage alternative energy is underappreciated.

This is not limited to Kalkuhl's paper: integrated assessment modelling, which informs much of the discussion on carbon pricing policy, treats innovation in a simple manner that does not reflect the true dynamics. For example, a common objection to reducing GHG emissions is that society should wait until technologies are cheaper before taking substantial action. While this has merits, it may be that technologies will not get substantially cheaper until they are are deployed, which obviates the reason to wait. Policies intended to spur innovation may unintentionally encourage lock-in, or prevent a superior technology from being adopted by promoting an inferior one. Even how to determine what a "superior" technology is requires an understanding of technological innovation. The complexity of innovation makes predictions and long term modelling difficult, and an understanding of innovation and its interactions with policy will help clarify the limitations of integrated assessment models for policy analysis.[Farmer and Trancik, 2007]

Lock-in and path dependency are important for policies beyond carbon pricing and integrated assessment models. It has implications for how science and R&D is funded, such as what factors should be looked for in a technology and how policies may cause unexpected side effects.

This essay will address the economics literature on technological lock-in and path dependency, to further illustrate its complexity and how policy interventions can have unanticipated effects. The conclusions found will be relevant to the literature on integrated assessment models, and provide a framework for modelling innovation that can be incorporated into integrated assessment models.

Chapter 2

Experience Curves

It has been repeatedly observed that cost decreases in many technologies follow an easily characterized trend, typically decreasing by some fixed percent with every doubling of deployment.[McDonald and Schrattenholzer, 2001] This gives rise to experience curves and progress ratios (PR's), a widespread way of characterizing learning-by-doing. An experience curve, or learning curve, is the trend line of a technology's cost plotted against cumulative deployment. This captures the decreases in cost as a technology is increasingly deployed. As cost decreases come from a particular form of use of the technology resulting in learning, the term *deployment* is used and typically corresponds to the production or construction of a unit of the technology rather than its continued use. An example for photovoltaic power modules is shown in figure 2.1. What is surprising, and typical of many technologies, is the linear trend line of the log-log plot over multiple orders of magnitude in cost and deployment.[Yeh..., 2007]

Both cost and deployment can be defined in multiple ways. Deployment will depend on the technology, and could be the number of items produced, such as cars, or production capacity, such as factories built. What is important is that the unit of deployment corresponds to the learning achieved by that deployment. Deployment is thus a stock, not a flow. Learning-by-doing is a complex process, originating from many sources. Employees may become more efficient, procedures improved, factories better designed, specialized training schools built, and innovations used, all contributing to decreases in cost. These cost decreases are related to the number of times the task which is being learned is repeated, and it is this repeated nature of the task that is important to capture in deployment. One

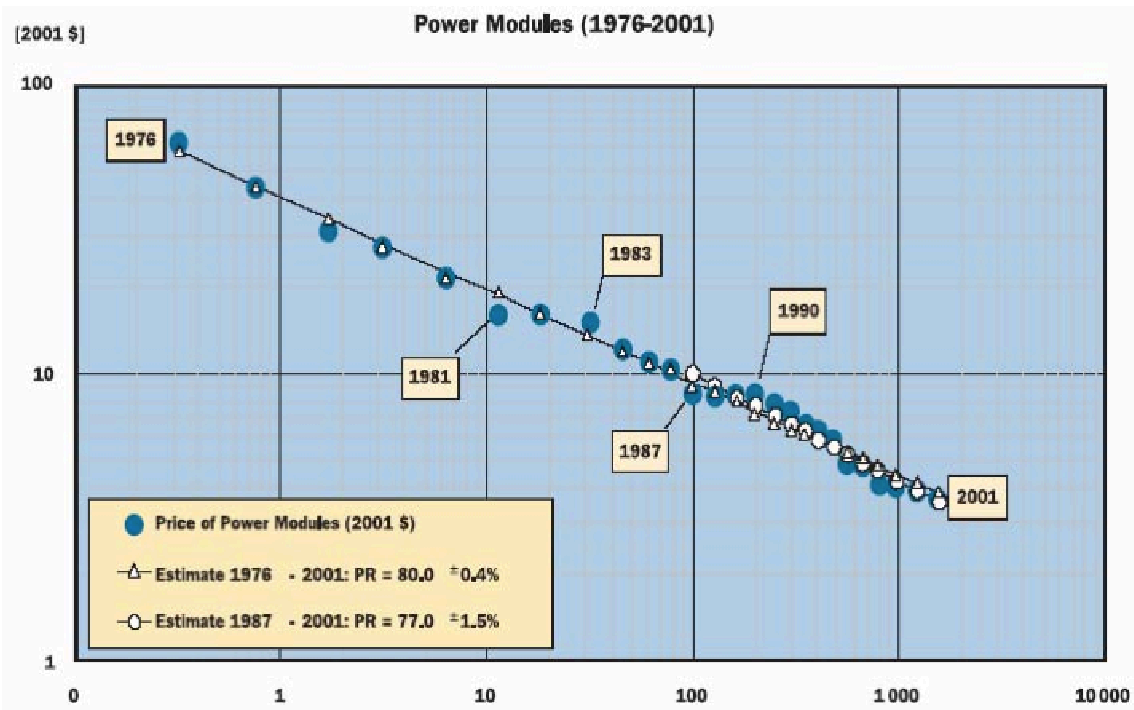


Figure 2.1: Cost vs cumulative deployment log-log plot for photovoltaic power modules.[NEEDS, 2007] Two progress ratio estimates are shown in the inset. The trendline is linear over several orders of magnitude in deployment quantity.

would not use the cumulative distance cars are driven as a measurement of deployment, as driving a car does not improve the ability of a car manufacturer to produce a cheaper car. However the number of cars produced, or factories constructed, is a suitable measure because most of the improvements will occur as additional factories and cars are constructed, and the organization learns to improve this process. Similarly, the quantity of electricity generated poorly captures learning in power plants, while the number of power plants built is a good metric.

Most of the learning occurs from designing, building, and operation of a plant. These may allow some cost decreases in this particular plant during its lifetime, but improvements are significantly constrained by what has already been built and what retrofits are possible. However this learning can be applied to the next iteration built, be it a power plant or car factory. In this way, the cost decreases are not realized by the agent performing the learning-by-doing until a new iteration of plant is constructed, to which the lessons learned can be applied. Learning is not restricted to one company or subset of the technology; there are substantial spillovers and communication that share learning and allow all agents to benefit from it.[Clarke et al., 2006]

As most of the cost of generating electricity comes from the fixed costs of the plant, as opposed to variable fuel and maintenance costs, once a plant is constructed it will continue operating even under competition from superior plants. Deployment does not represent the replacement of an old plant by a new one, but a combination of retiring of obsolete plants combined with new expansion.

True cost data is usually not available from companies, so the price of a product is often taken as a proxy for cost. This cost as a function of cumulative deployment is fit with a power law. The cost C is a function of the cumulative deployment D, the initial cost C_o, and a constant α. The progress ratio is defined as the percentage of the original cost remaining after a doubling of deployment. Thus, if after a doubling of deployment, the new cost is 80% of the previous cost, the PR is 0.8. Typical progress ratios are in the range of 70% - 90%, and stay reasonably constant for a specific technology throughout a wide range of deployment quantities.

$$\begin{aligned} C &= C_o(D)^\alpha &(2.1)\\ \frac{C_2}{C_1} &= \frac{C_o(2D)^\alpha}{C_o(D)^\alpha} = 2^\alpha &(2.2)\\ PR &= 2^\alpha &(2.3) \end{aligned}$$

Comparisons of progress ratios between technologies are dependent on a consistent measurement of deployment and cost, which can be problematic. For electricity, comparisons are simpler, given the fairly consistent definitions of deployment and cost. Deployment is given by mega-watts (MW) of installed capacity, which is the generating size of a power plant. A given type of power plant will vary substantially in generation size. These plant sizes are similar enough in their technical properties that the economic literature aggregates installed capacity in MW over many plant sizes as the measure of cumulative deployment.

Comparisons between dissimilar electrical generation technologies, such as gas and wind, must account for differences between the technologies that complicate definitions of deployment and cost. In particular some sources are highly variable, such as wind, while others can dispatch power on demand, such as gas. A significant cost of fossil fuel power generation is the fuel, while the up front plant costs are relatively small. In contrast, most alternative energy has very low fuel and maintenance costs, with high up front costs. To enable comparisons, technologies are compared through levelized cost estimates. Levelized cost is the long-term price of electricity sold by a generation source in order for it to break even. This price includes all costs over a power-plant's lifetime, such as the discounted cost of capital, maintenance, fuel, etc, and corresponds to what price an investor would have to sell electricity at to break even.

Chapter 3

Model Description

Experience curves provide a way to characterize technological change and forecast costs, as well as demonstrate decreasing costs, lock-in, and other dynamics resulting from a simple model of technology deployment.

An agent-based model is used to generate experience curves to demonstrate the complexity of innovation and the sometimes unexpected results of policy interventions. The model consists of several technologies and a selection of agents who decide which technology to invest in via deployment. Agents consider a combination of technology costs and their own intrinsic (and usually different) preferences among technologies. Agents thus function both as electricity utilities and governments in deciding between technologies to invest in. The agent then deploys some exogenous quantity of the chosen technology to meet society's demand for energy. The quantity of energy demanded will vary endogenously, such as energy demand being affected by energy prices. As the model deals with changes between technologies due to their relative prices, and society's demand for energy is largely determined by demographics and the degree of society's development, it is reasonable to consider an exogenous energy demand which determines the quantity to be deployed.

It is the dynamics of deployment between technologies that is of interest in this model. If the quantity deployed increases or decreases, this will affect the time scales over which deployment dynamics happen, but not the dynamics themselves. This is an additional reason why the quantity demanded, and deployed, is taken as exogenous. The exogenous demand is taken as linear over the time frame of interest. While true energy demand,

and deployment, is not expected to be linear, a non-linear function complicates modelling and only modifies the time scale of model dynamics. As this is not of interest, a linear exogenous demand is used.

The technology deployed adds to the cumulative deployment, and reduces the cost of the chosen technology. In the next time period, agents again examine the selection of technology costs along with their individual preferences and choose which technology to deploy. In the case of electricity generation, this deployment can represent the building of a new power plant to either expand generation capacity or replace worn out plants. Learning will occur over the lifetime of the plant, but cost decreases cannot be realized until the next iteration of plant is constructed. In considering costs, agents thus only consider the current NPV of the technology investment, represented by its levelized cost. A plant constructed at a given cost will likely continue producing electricity at that cost for its lifetime, but this is not relevant to experience curves.

Each technology is defined by its progress ratio and initial cost, C_o. To simplify modelling, C_o is defined as the cost at the initial deployment when t=0, not when D=0. The model iterates over a series of time steps, with agents deploying some quantity Q to increase the deployment dependent on the previous cost and preferences. The new cost for that time period is then calculated, and the model advances to the next time step. Thus, cost is a function of the previous stock of deployment, as in the standard experience curve.

At t=0, each technology has an initial cumulative deployment quantity D_o. In a model with one technology and one agent deploying Q in each time period, the cumulative deployment D would evolve as:

$$D_t = D_{t-1} + Q \tag{3.1}$$

$$D_t = D_o + \sum_{j=1}^{t} Q \tag{3.2}$$

And cost as:

$$C_t = C_o(D_t)^{\alpha} \tag{3.3}$$

Instead, there are multiple agents and multiple technologies between which each agent must choose. For two technologies, this is implemented as the agent choosing the maximum combination of a technology's cost and their preference for it.

$$Max \begin{cases} Pref_1 - C_{t,1} & \text{Technology 1} \\ Pref_2 - C_{t,2} & \text{Technology 2} \end{cases} \tag{3.4}$$

Preferences are thus expressed in terms of a technology's cost, and an agent has a preference for each technology. In addition, it is the difference between an agent's preferences that is important; preferences are a relative measurement only. Whichever technology has the highest $Pref - Cost$ combination, is the one the agent deploys. An agent's preferences represent the factors influencing an agent's decision that that are not captured by levelized costs. This could be practical considerations, such as limitations in suitable construction sites sharply increasing costs, or a more subjective desire for one energy source over another, such as gas generation over nuclear, despite similar costs.

At each time step, each agent will look at the technology's cost and their preferences and made a decision on which technology to deploy Q to. That technology's cumulative deployment will increase, and the new cost C_t will be updated. The model will advance to the next time step, and the agent will again evaluate costs and preferences and deploy a quantity Q. With two technologies and one agent, the agent will always only choose whichever technology was initially cheaper. This technology will continue to decrease in cost, while the other remains fixed at C_o.

With two technologies and two agents the situation is more complex. Consider two technologies, one that is new and expensive but decreases quickly in cost with deployment, and a second that is old and inexpensive, but decreases little in cost with additional deployment. Which technology is superior depends on how one defines superior. Here, superior will mean the technology which would have reached the lowest cost over the time period considered assuming it received all the remaining deployment. This is almost always that technology with the smallest progress ratio.

Along with the two technologies there are two agents; an indifferent agent who has no preference between the technologies, and so chooses the cheapest, and one whom we'll call the ideological agent, who strongly prefers the expensive technology. Initially, the indifferent agent chooses the old inexpensive technology, and the ideological agent chooses the expensive one. Over time, the expensive technology may decrease in cost sufficiently to catch up to the old technology, and eventually pass it. This newer technology, formerly more expensive, is now the cheapest. At this point, both the ideological and indifferent agents will choose the new technology. There is no additional deployment to the old technology, its cost remains constant over time, and the new technology continues to decrease in cost. This is the simplest form of transition between two technologies, and break-out from lock-in.

3.1 Model Implementation

The model was programmed in MATLAB, with the computer code available in the essay appendix. Implementation of this model proceeds as follows:

1. Initialize model parameters.
    - Set PR's, initial costs, and deployments
    - Set agent preferences
    - Define deployment quantity to be deployed by each agent
    - Define array of time over which to iterate
2. Time step iteration
    (a) Begin iteration over each agent
        - Choose technology based on agent preferences and previous step cost
        - Increase that technologies cumulative deployment by Q

    (b) Complete iterations over each agent

    (c) Calculate new cost for each technology at current time step

    (d) Begin next time step iteration
3. Complete iterations over all time steps.
    - Display results and experience curves

3.2 Preference Distributions

More than two technologies and agents are included by iterating over multiple agents and technologies. For larger numbers of agents, one can speak about the distribution of preferences for the various technologies. A technology may have no agents preferring it, resulting in all agents considering it only based on cost. A technology may have a subset of agents preferring it (positive preference value) or disliking it (negative preference values) or any combination.

For example, consider five agents choosing between three technologies, table 3.1. Agents #1 and #2 are indifferent to the three technologies, having no preference for any of them. Agents #3 and #4 slightly prefer technology 2, while #5 strongly prefers both technology #2 and #3 compared to #1.

	Preference		
Agent #	Technology 1	Technology 2	Technology 3
1	0	0	0
2	0	0	0
3	0	1	0
4	0	1	0
5	0	3	3

Table 3.1: Array of preferences for 3 technologies and 5 agents.

The model considers large sets of agents with smooth variations in their preferences. To do this, a set of agents is defined by the number of agents, the mean and standard deviation of a gaussian distribution of preferences for each technology being considered, and an increment between preference values to discretize the preferences. This allows the distribution of preferences for each technology to vary independently. The gaussian preference distribution is generated for each technology and the number of agents with a given preference value is determined from the density of the distribution at that preference, see figure 3.1. The preferences for each agent are combined, generating an array of the individual preference values across a technology. The process is repeated for each technology, and can be repeated for multiple groups of agents. This allows complex preference distributions to be generated, for example having a large group of agents generally indifferent to a technology, along with a small group of ideological agents demonstrating strong preferences, as in figure 3.2.

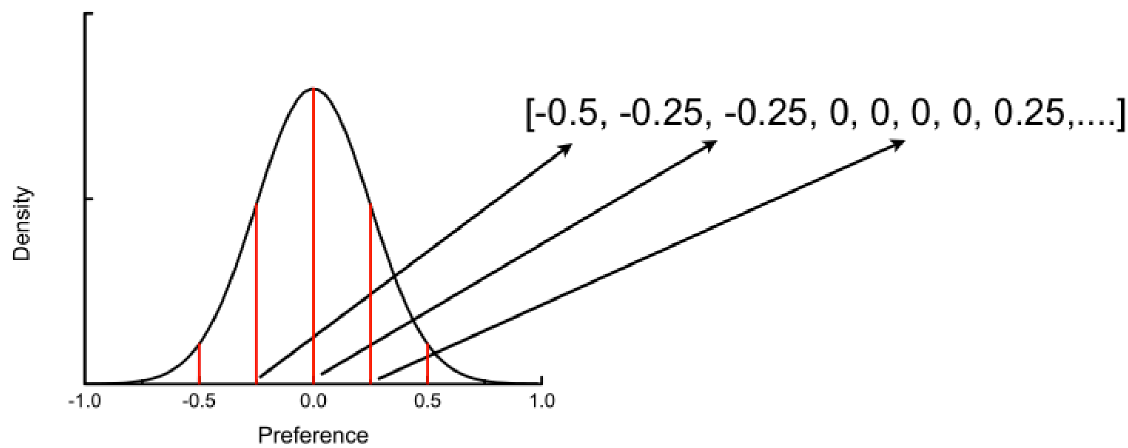


Figure 3.1: Generating an array of preference values from a gaussian distribution of preferences. The gaussian distribution of preferences is determined (black curve), and the density of agents determined for chosen preference values. The number of agents with a given preference is found, and combined to form an array of agents with individual preferences for the given technology.

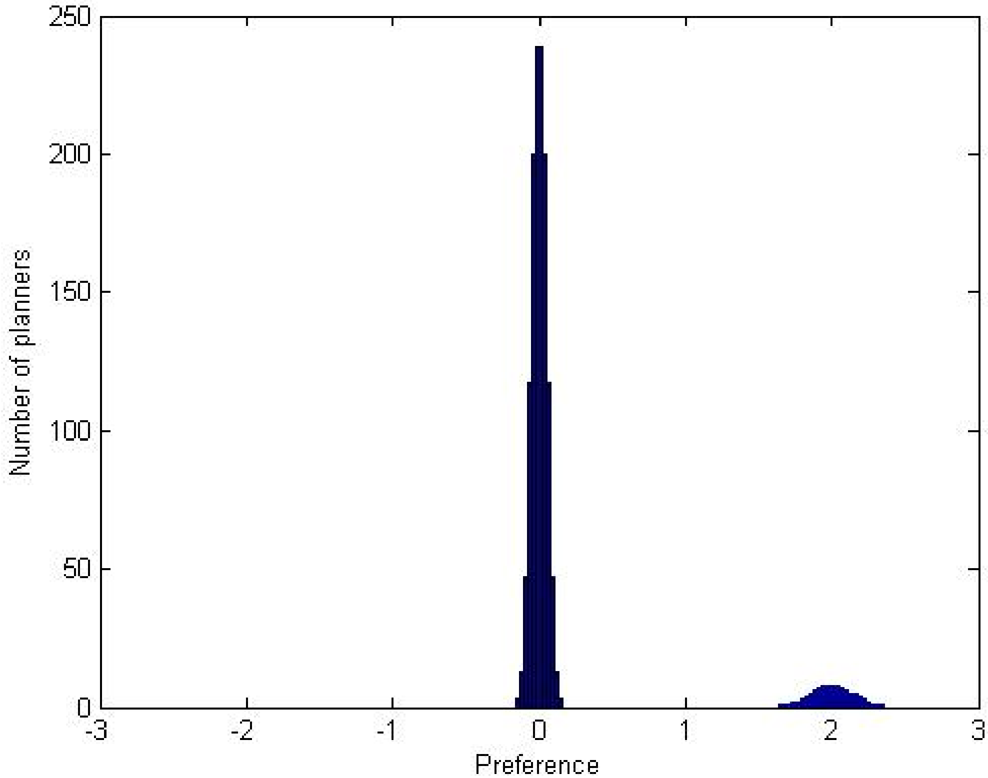


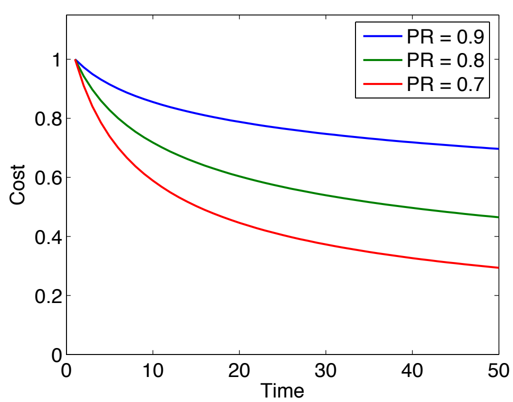
Figure 3.2: Histogram of preferences for a technology, showing a central group of 1000 largely indifferent agents, and a small group of 100 ideological agents. Histograms generated from preference distributions of 1000 agents, SD 0.05, mean 0, and a second group of 100 agents with SD 0.2, mean 2.

Chapter 4

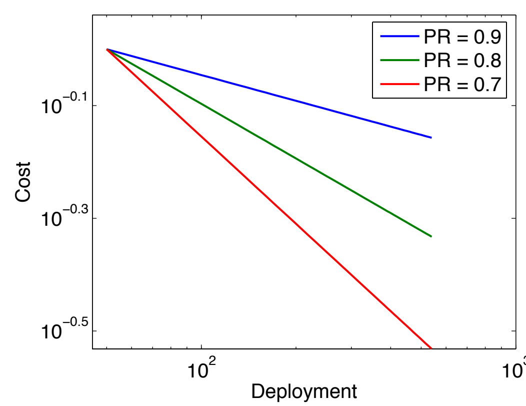
Model Results

4.1 Experience Curve Properties

Before discussing the model dynamics, several properties of experience curves will be demonstrated. Cost decreases are highly sensitive to the progress ratio. Figure 4.1 shows the experience curves at three progress ratios, plotted both against time and cumulative deployment. The large early cost decreases are a result of the low initial deployment relative to deployment in each time period, here a 5-1 ratio.



(a)



(b)

Figure 4.1: Cost decreases at three progress rates. (a) shows the cost decreases vs time, while (b) shows the corresponding log-log plot with linear experience curves.

As cost decreases come from cumulative deployment, the initial deployment at t=0 has a strong effect. Experience curves in figure 4.2 have the same PR, but with different initial deployments of 100, 10, and 1, relative to a deployment in each time step of 1. Clearly a high initial cumulative deployment sharply reduces the effect of further deployment. The initial cost C_o changes the y-offset but not the experience curve shape, as in figure 4.2 (b).

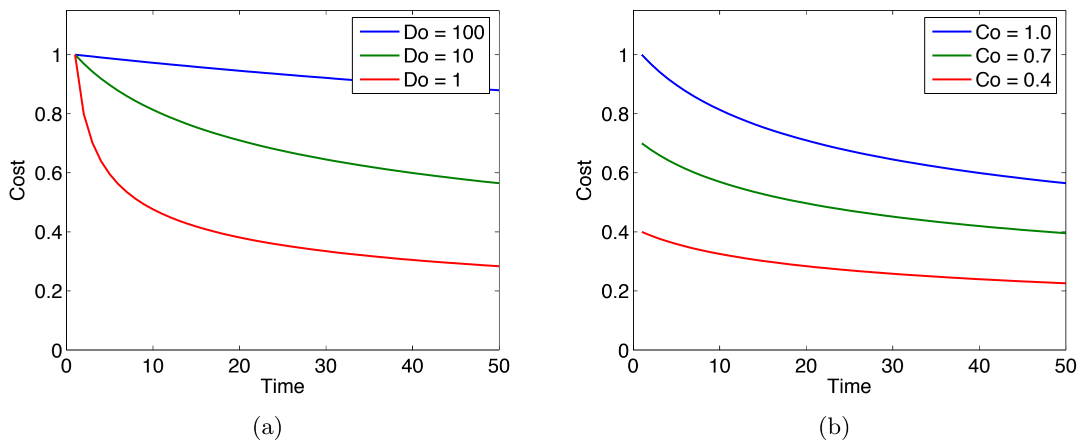
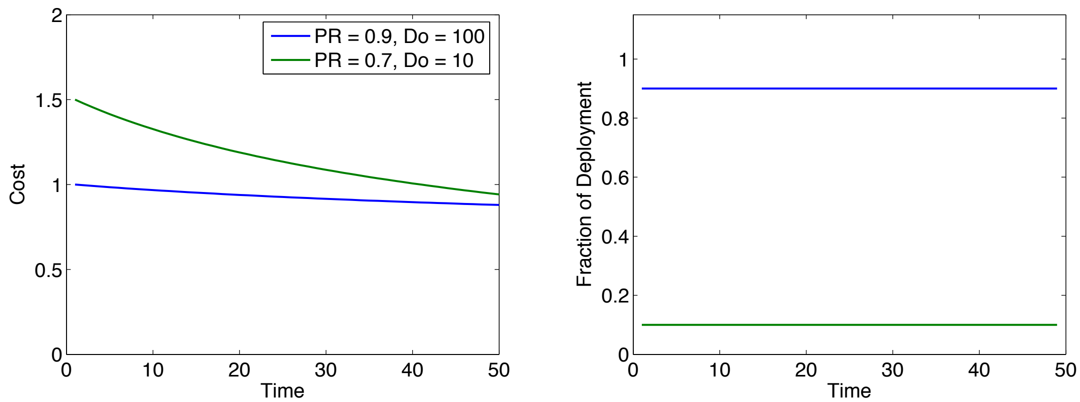


Figure 4.2: (a) Cost decreases at the same PR, but with different initial deployments. (b) Cost decreases with the same PR and initial deployment but a different Co.

4.2 Transitions between Technologies

The previous plots did not include the possibility of transitions between technologies as deployment to a given technology was fixed. The simplest form of transition can be demonstrated using two technologies and two sets of agents with different preferences. There is one large group of indifferent agents who decide on cost, and a smaller set of ideological agents who prefer the more expensive ('new') technology. The model of this is shown in figure 4.3 and figure 4.4. With 10% of agents initially deploying to the expensive technology, (4.3) it remains more expensive throughout the time period but steadily decreases in cost. The fraction of agents deploying to each technology remains constant, as seen in 4.3 b.

With an initial 20% of agents ideologically choosing the more expensive technology, (4.4) its cost decreases faster, until at $t \sim 28$ the initially expensive technology has become

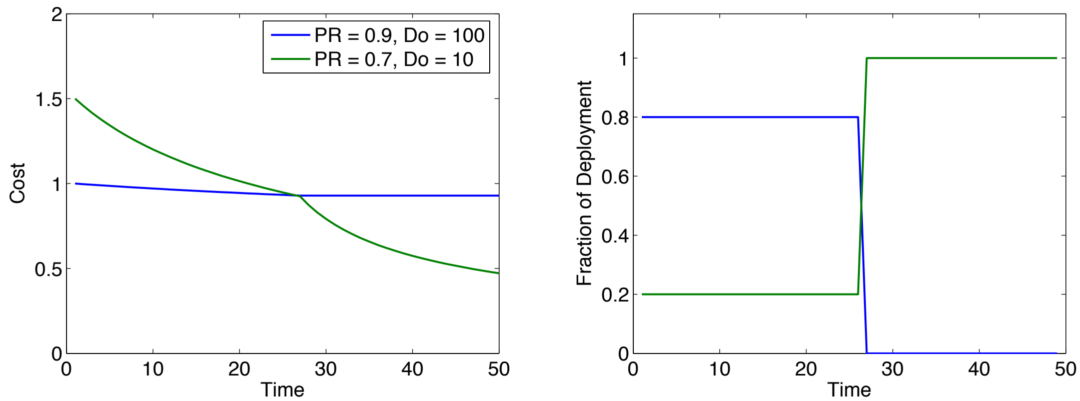


(a) (b)

Figure 4.3: (a) 10% of agents initially deploy to the PR = 0.7 technology. Costs decrease for both technologies throughout the time period shown. (b) The fraction of agents deploying to each technology remains fixed.

cheaper than the established one. At this point, the newcomer technology experiences a sudden decrease in cost, as the indifferent agents begin deploying it and generating new learning-by-doing. This can be seen in 4.4 b, where after remaining constant the fraction of agents quickly changes, reaching 1 for the new technology.

This change from no crossing of costs to crossing with a substantial decrease in the cost of one technology, dependent on a relatively small change in the number of ideological agents, is an example of lock-in. The old technology is cheaper than the newcomer, attracting most agents, and preventing the newcomer from reducing sufficiently in cost to compete in the time period being considered. When the newcomer technology does decrease in cost sufficiently to compete based on price, it suddenly attracts a large market share and lock-in is broken. This illustrates the danger of modelling technological progress as a simple progressing improvement; sudden changes in trajectory can occur. Additionally, a retrospective experience curve analysis if plotted in the conventional log-log plot cost vs deployment will not show such dynamics; they exist only when one examines the cost over time.



(a) (b)

Figure 4.4: (a) 20% of agents initially deploy to the PR = 0.7 technology. At t $\simeq$ 28, the 0.7 technology breaks lock-in. (b) The fraction of agents for each technology. At t $\simeq$ 28, the previous lock-in is broken, and all agents switch to the new 0.7 technology, establishing a new lock-in.

4.3 Similarity between Technologies and Products

The similarity between competing technologies is important for lock-in. Technologies may differ both in their technical aspects and in the good they produce. The form of similarity has a strong impact on the risk of lock-in and the need for policy intervention.

The simplest case is two similar technologies producing an identical good. In this case, the technologies will compete almost completely on cost. This is close to the situation for nuclear power plant designs, which produce completely complementary electricity, and have similar fuel, water, and site requirements. However the design may differer substantially in potential efficiency, safety, or other aspects. Experimentation with additional designs is expensive given the facility cost. Technologies like nuclear power are vulnerable to lock-in, due to the difficulty of experimentation and their lack of niche markets.

As technologies begin to differentiate, they begin to compete in ways other than strict cost. For example, solar and coal are vastly different technologies which can produce identical electricity. However they are each uniquely suited for some applications, such as solar for distributed sites and remote locations, and coal for stable base-load power. This gives each technology a niche application. As differentiation between technologies increases, a large percentage of customers may not be able to use one technology, regardless of the cost. For example, hydroelectric power is simply unavailable in areas without suitable rivers.

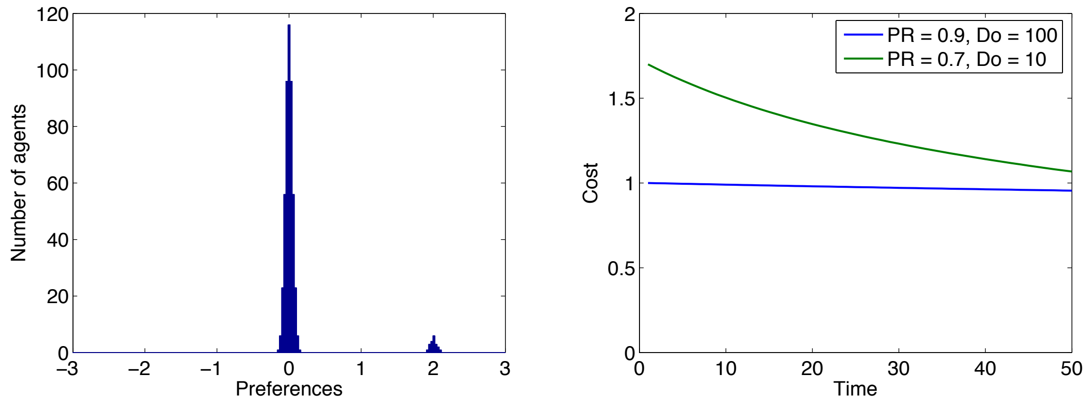
In addition to the technical differences, the good produced may differ. In the limit of technologies differing in their products, there is no competition between the technologies. For dissimilar goods, the situation is again one where some customers may decide based on price, but technology specific preferences will be important. For electricity, this is similar to the case of dispatchable vs variable power generation, that is energy available on demand, and energy available when the conditions (sunlight, wind, etc) are right. While both may be able to compete based on price, they can only do so in limited quantities.

The differentiation in technology or product is important for generating niche markets. Niche markets have a strong impact on lock-in, by generating learning-by-doing for a technology to some degree independent of its price.

4.4 Niche Markets

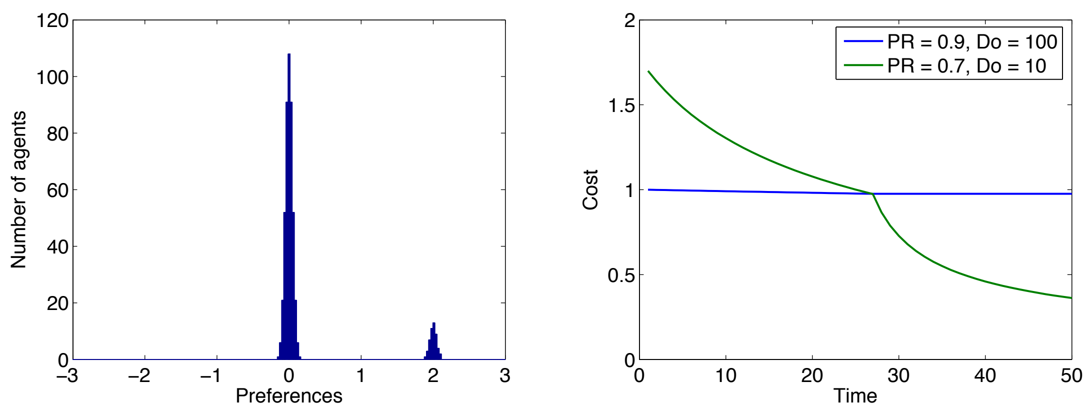
Niche markets are important, as they maintain demand for an initially expensive technology and reduce costs via learning-by-doing. For an established technology competing with a more expensive newcomer, niche markets can be represented by a subset of agents with strong preferences for a technology. In the case of no niche market, equivalent to all preferences being 0, all agents decide based between technologies based on price only. This results in complete lock-in, where the initially cheapest technology attracts all investment and cost decreases.

With a small niche market, here 4% of the total, some demand for the new technology is maintained and it reduces in price, figure 4.5 (b) If the niche market increases to 8% of the total market, the increased deployment reduces prices until lock-in is broken, figure 4.6. A wide distribution of preferences functions similarly to a niche market, figure 4.7.



(a) (b)

Figure 4.5: (a) Histogram of preferences for the new (PR=0.7) technology, showing the majority of agents are indifferent to the technology, while a small niche market exists as shown by the agents with preferences near 2. (b). The niche market is too small to generate cost decreases sufficient to break lock-in.



(a) (b)

Figure 4.6: (a) Histogram showing a larger niche market compared to figure 4.5. (b) Lock-in is broken.

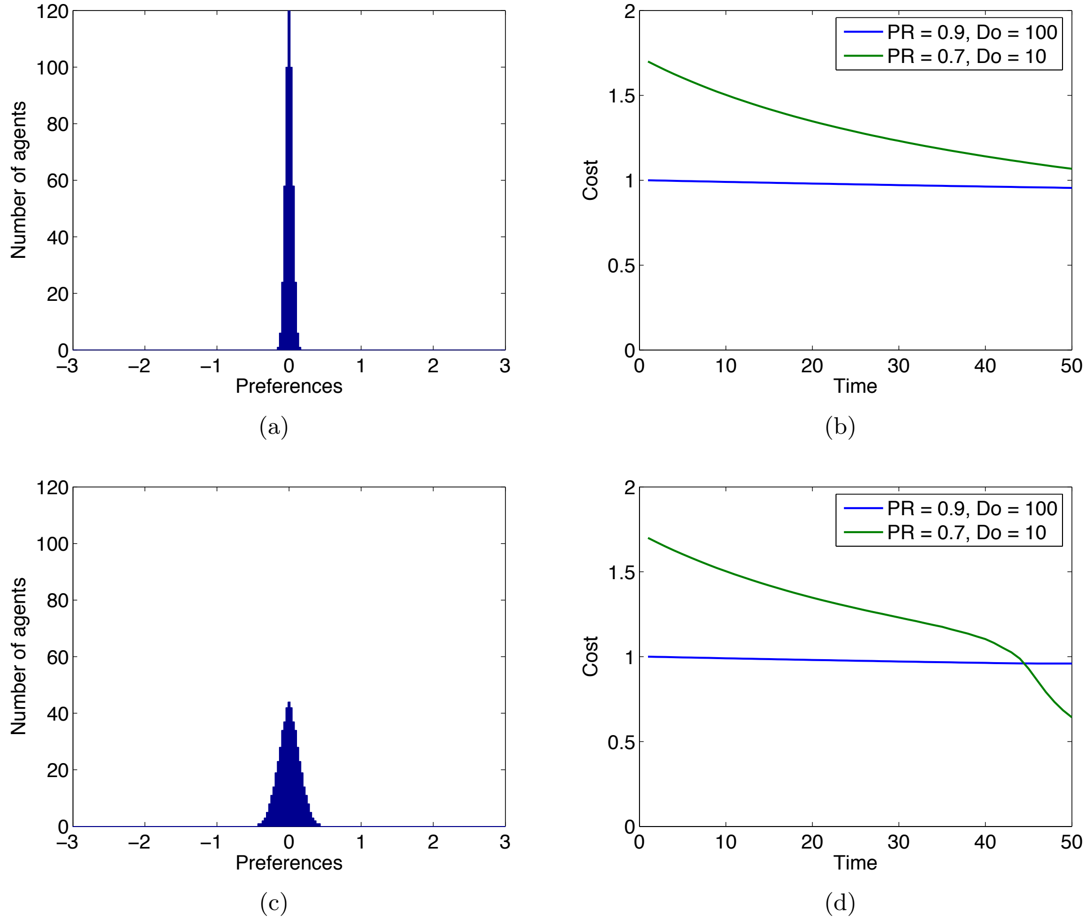
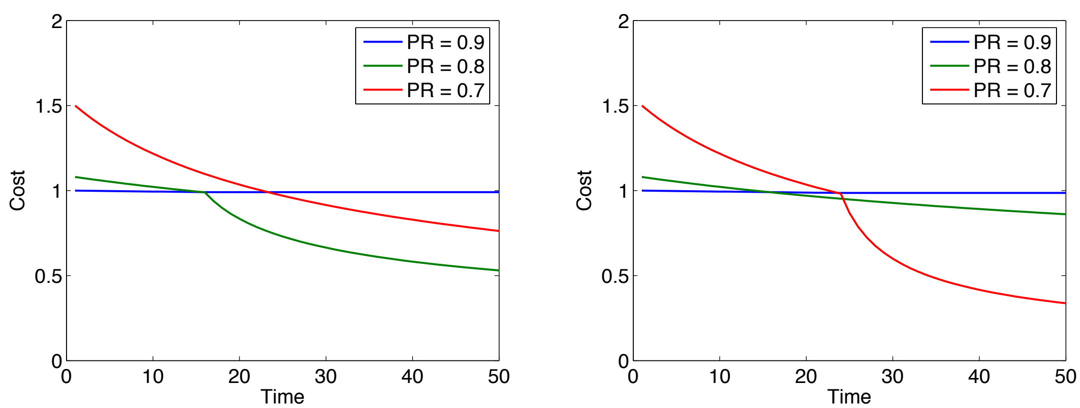


Figure 4.7: (a) A narrow distribution of preferences for the PR = 0.9 technology. Not shown is the niche market for the PR = 0.7 technology. (b) Corresponding cost decreases. (c) A broad distribution of preferences for the PR = 0.9 technology, with the same number of agents and niche market. (d) The broad distribution causes some agents to switch technologies earlier, breaking lock-in earlier than with a narrow distribution.

4.5 Competition between Multiple new Technologies

Competition between multiple new technologies significantly complicates issues of lock-in. There is a risk of breaking the existing lock-in but establishing another lock-in of an inferior but new technology over an also new but superior competitor. Lock-in can occur in different ways. Consider two new technologies competing with each other and an established technology, figure 4.8. Both newcomers have the same small niche markets, and one has an inferior PR rate (0.8) while the other is superior (0.7). If both technologies are introduced at the same time but the inferior technology has a lower C_o, or alternatively the inferior (PR = 0.8) technology is introduced first, the lower PR technology can be the first to reach competitiveness with the existing high PR (0.9) technology. At this point, the majority of agents, who previously used the low-cost technology, switch. This new PR = 0.8 technology is now locked-in. However if adoption of this technology is delayed in favour of the higher-learning (0.9) technology, it quickly catches up and surpasses that of the inferior PR technology, resulting in ultimately lower prices, as in figure 4.8.



(a) (b)

Figure 4.8: (a) Three competing technologies with a new lock-in of the new PR = 0.8 technology. (b) Widespread adoption of the PR = 0.8 technology is prevented, causing the PR = 0.7 technology to break the existing lock-in.

Some of these lock-in and competition issues can be demonstrated by considering current alternative energy. Solar electricity is the most promising alternative energy technology for ultimately producing large amounts of cheap, clean, electricity. Wind, tidal, and biomass are all limited by the potential energy available in the wind, tides, waves, and biomass, as well as absolute physical restrictions in the amount of area available for deployment, let alone the smaller subset which is economically viable. Geothermal has potential, but is still limited to areas with heat sources close to the surface. In contrast, sunlight, captured over reasonable areas of the earth at reasonable efficiencies, could provide enough energy to cover society's growing energy needs. In addition, solar offers solid potential for improvement. While wind is currently cheaper, it is questionable for how much longer. Technologically, solar has the potential for much larger improvements than wind.

The relatively large differences between solar and wind technologies provide opportunities for niche markets, and lock-in between them is unlikely. Lock-in is more of a risk, however, among the numerous competing similar solar technologies at various stages of commercialization and experimentation. These include well over a dozen demonstrated designs of solar panels which are often based on very different materials and physics; several solar thermal designs, where sunlight either produces steam to drive a turbine, or runs a Stirling engine; and recent artificial-photosynthesis cells, which use chemistry to capture sunlight, either producing electricity or directly converting sunlight into a liquid fuel. Unlike comparisons between solar and other technologies, there exist relatively few niche markets between competing solar technologies. The ultimate technical potential of many is not yet apparent. Some have a long history of commercialization, others are just coming on the market, and a few are still only theorized. In addition, jurisdictions are instituting a variety of aggressive policies in support of alternative energy. This combination of factors makes alternative energy technologies vulnerable to lock-in among themselves, and a consideration of policy interventions is needed.

Chapter 5

Policy Interventions

For the general problem of lock-in, both competition between an established technology and newcomers, and between multiple newcomers, is of concern. Because cost decreases exhibit strong decreasing returns to scale in deployment, it is possible for a superior technology to achieve cost decreases sufficient to catch up to an established but inferior technology. Breaking out from lock-in becomes a policy question of how much society wishes to spend to encourage cost decreases of the new-comer, and to what extent niche markets exist to maintain demand. For general alternative energy compared to established fossil fuel technologies, there is currently rapidly growing deployment and corresponding significant cost decreases. Policy interventions are a result primarily of concerns about GHG emissions, rather than a concern of lock-in of established technologies. It is more of a question of how soon, determined from considerations of CO2 emissions, does society want to break the lock-in of fossil fuels.

However, there is still a large risk of lock-in between alternative energy technologies. Here policy may have a large impact on which technologies are ultimately adopted. Although various policies such as carbon taxes and subsidies have been considered at length in terms of their tax and fiscal qualities, their effects on lock-in have not been studied.

The difficulty of "picking winners" is well known, and is a common argument in favour of using markets where possible. It is also a key issue for policies addressing innovation. A policy may help a technology quickly reach commercialization or widespread adoption, or conversely be directed at an ultimately inferior technology, wasting time and money.

Thus the degree of technology discrimination of a policy is important. At one extreme, this may be a policy such as a subsidy targeting a specific technology, on the other it may be a broad policy supporting specific goals, but not specific technologies, like a carbon tax. How and when policies influence a technology's development is important for design of efficient policies, and avoidance of future undesirable lock-in.

Because of lock-in and path dependency, policies may have unexpected effects that must be considered in policy design. Integrated assessment models often evaluate policies, and without consideration of lock-in may give erroneous conclusions. This is demonstrated through experience curves generated by the agent-based model.

5.1 Feed-in Tariffs

Feed-in-tariffs (FIT's) are a form of subsidy that guarantees a long term price support to technologies. A subsidy is provided to either the consumer or producer in order to reduce the cost the consumer pays to the producer, making the product cheaper. The FIT may give different prices to different technologies, and include a decrease in the amount of the subsidy over time. Typically they guarantee a constant ROI among different technologies, as opposed to a constant price for the product produced. FIT's have been used in over 50 countries to encourage the deployment of alternative energy technology, including in Canada. FIT's typically provide a subsidy for a long time period, such as 20 years, judged to be sufficient to make a particular technology commercially viable. FIT's typically decrease over time to encourage technological innovation, track decreases in energy costs, and to reduce the cost of the subsidy.

The degree of technological discrimination is key in implementing an efficient subsidy. Too broad, and it may subsidize inferior or unsuitable technologies. Too narrow, and it risks accidentally supporting only inferior technologies and potentially contributing to lock-in. The simplest subsidy uniformly reduces the price of some subset of technologies. In addition to the degree of technology discrimination, a subsidy is only effective if it results in additional deployment to that which would have occurred otherwise. This can be seen by considering two technologies: a high learning newcomer and an established competitor. In figure 5.4, the introduction of a 20% subsidy has a drastic effect on a technology's evolution. With no subsidy, the newcomer technology does not break even over the 50 year time span. With the 20% subsidy, it undergoes a rapid cost decrease, quickly supplanting the established technology.

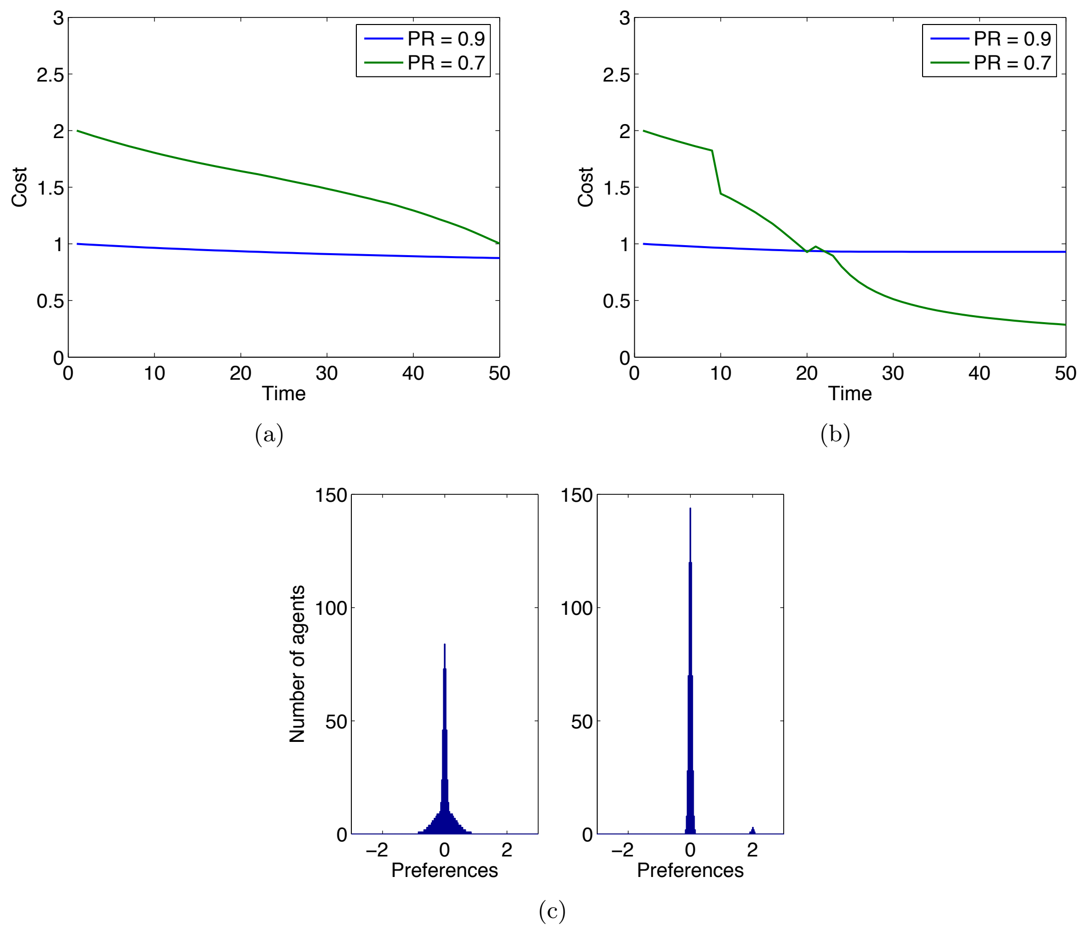


Figure 5.1: (a) No subsidy. (b) 20% subsidy applied between t = 10 and t = 20. (c) The preferences for the PR = 0.9 and PR = 0.7 technologies. A small niche market of %1.7 of the total agents exists with preferences near 2 for the 0.7 technology, visible as a small histogram.

This drastic change is dependent on several factors. Clearly the newcomer technology must be of relatively high learning rate, or the subsidy of sufficient strength over sufficient time in order to have a significant effect. The distribution of preferences for a technology also plays an important role. With a narrow distribution of preferences for the established technology, most agents choose between them based only on price. A subsidy causes a significant drop in price, but little increased adoption as the technology is still more expensive than the competitor. Costs do not decline significantly, and the subsidy then ends with little long run change in the technology's trajectory. With slightly larger tails to the distribution of preferences, there are more agents partial to the newcomer technology. When a subsidy is implemented, the new technology is affordable, and they adopt it. This causes further cost decreases, such that even when the subsidy is removed the technology has broken lock-in and overtakes the established competitor, figure 5.2

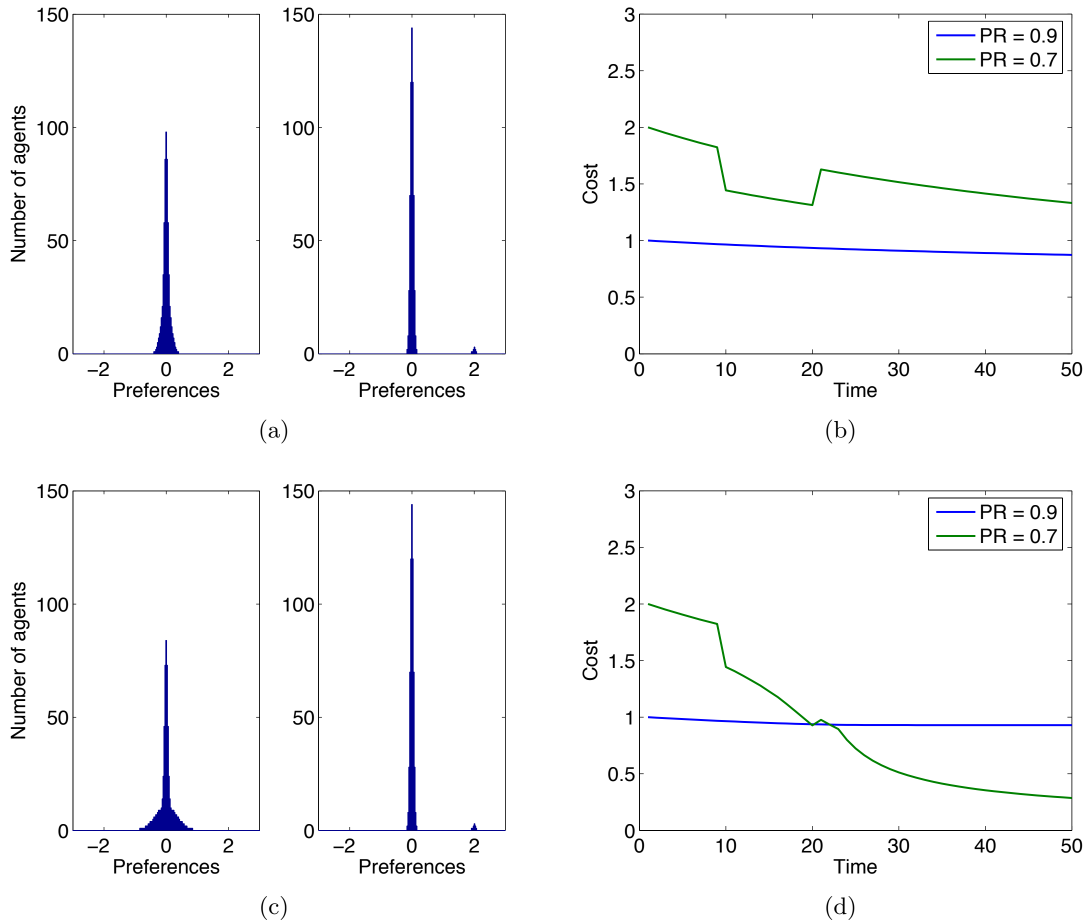
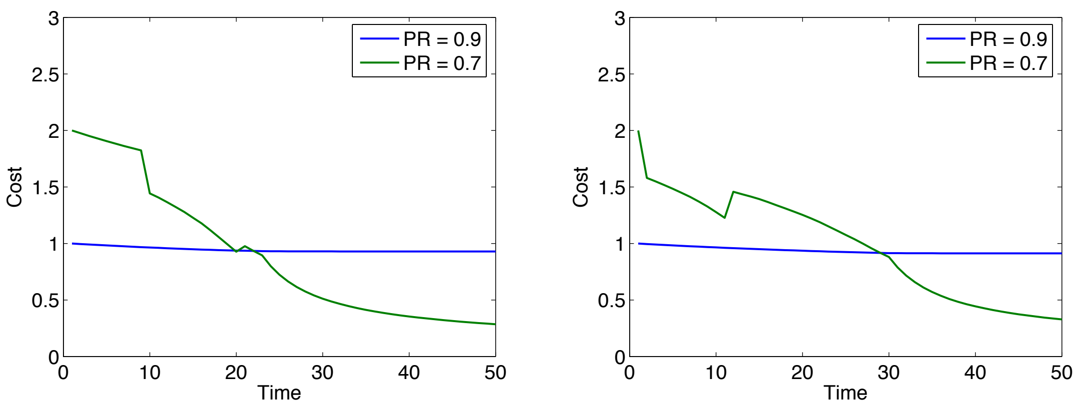


Figure 5.2: The effect of a subsidy is dependent on the number of agents switching technologies due to the subsidy. (a) A narrow distribution of agents, with (b), a corresponding lack of long run changes in cost decreases due to the subsidy. (c) A broader distribution of preferences, and resulting long run changes in cost, (d).

5.2 Timing of a Policy Introduction

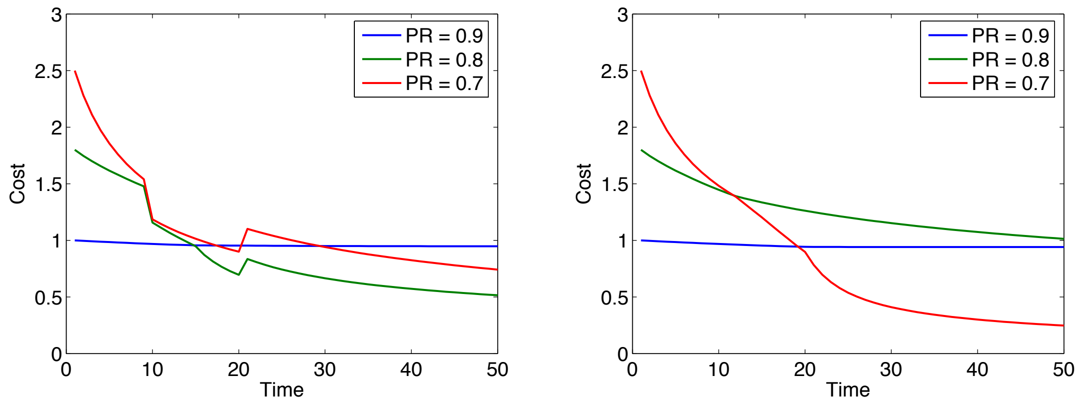
That the effects of a subsidy are dependent on when it is introduced is not surprising. A subsidy introduced too late will have little beneficial effect if the subsidized technology is already competitive. Similarly a subsidy introduced too early can also be inefficient. A subsidy introduced too early causes few additional adopters, though it is sufficient to break lock-in. A later subsidy, introduced after additional cost decreases due to the niche deployment, causes a larger additional adoption, and similarly breaks lock-in. Surprisingly, the earlier subsidy breaks lock-in later than that subsidy introduced later. This is because much of the benefit of the subsidy introduced early is lost if no additional agents choose the new technology.



(a) (b)

Figure 5.3: The effects of a subsidy introduced at t = 10 (a) and t = 1, (b). The subsidy introduced earlier causes a later transition between the two technologies.

Additional effects can arise when more than one newcomer technology is competing. In this case, both new technologies may have niche markets, and be improving. One is superior, yet has been introduced later and so is currently more expensive than an earlier introduced, but ultimately inferior, competitor. With no subsidy, the superior technology eventually decreases in cost sufficiently to pass the inferior but introduced early technology, and break lock-in of the established technology. A subsidy can interrupt this process, lowering the price of both technologies such that the introduced early technology becomes competitive and breaks lock-in of the established techology. The additional deployment results in sufficient cost decreases that the inferior technology locks-in itself.



(a) (b)

Figure 5.4: A subsidy introduced at the wrong time can cause a transition to an inferior technology (a) where no subsidy would allow the superior technology to break lock-in of the established (PR = 0.9) technology, (b).

Similarly, a subsidy supporting only a subset of new technologies can increase the likelihood of lock-in, penalizing new technologies which are not yet cheap enough to convince a government to subsidize them. Such support can arise for political reasons, or because governments want to support a seemingly successful technology.

5.3 Carbon Pricing

A carbon tax will be considered in the context of an established fossil fuel locked-in technology competing with a suite of more expensive but carbon-free technologies. The tax raises the price of established technologies, and has a similar effect to a broad equal subsidy of all new technologies. It is still superior to a broad equal subsidy, as it does not require one to define and include new technologies; they are supported by default. However, similar to a broad subsidy, a carbon tax does not help ensure that a superior new technology will be the one widely adopted.

Ideally a carbon tax will raise the price of the established technology, making a competitor more attractive, and reduce the time taken until the existing lock-in is broken, as in figure 5.5. However, it can have a similar undesirable effect to that of a subsidy in causing adoption of an inferior new technology, illustrated in figure 5.6. At first glance this does not appear a significant problem, as the carbon tax has helped a cheaper technology break the pre-existing lock-in. The downside results from the orders of magnitude difference in deployment that occurs between the cheapest technology and competitors. This establishes a new lock-in which may not be broken for a significant time.

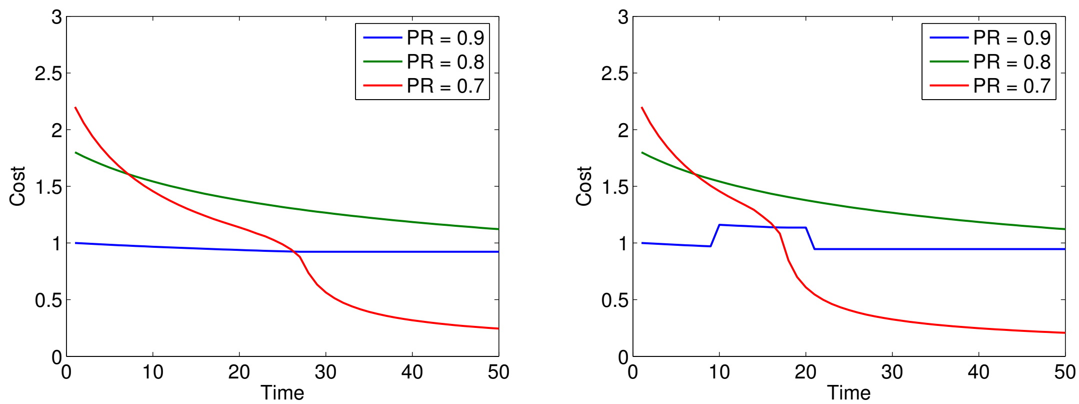


Figure 5.5: (a) The business as usual case with no carbon tax. (b) A carbon price reduces the time taken for a superior technology (PR = 0.7) to break lock-in.

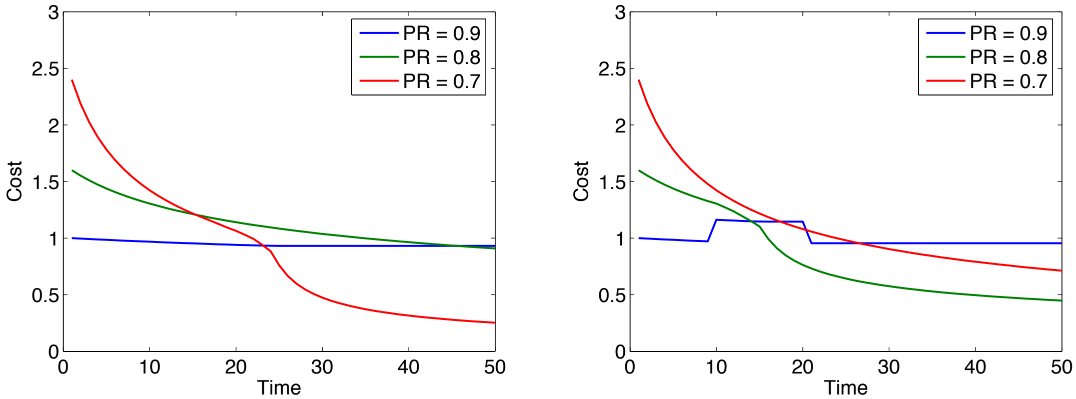


Figure 5.6: When a superior technology (PR = 0.7) will break lock-in, (a), a carbon price can instead cause an inferior technology to be widely adopted, (b).

5.4 Optimal Policy

In deciding which policy is optimal, many aspects will have to be considered. Taxation, legality, practicality, and the goals of the policy, in addition to its effects on technological innovation. For the aspects relevant to this essay, an optimal policy for encouraging innovation will need to balance several sometimes conflicting goals. It should not penalize technologies introduced later, it should differentiate between technologies to recognize their different stages of development, and it should be broad based, to avoid excluding technologies purely due to regulatory definitions rather than technological reasons.

Direct subsidies targeted at a few chosen technologies, such as those for carbon capture and storage, should be avoided, as their benefit of encouraging deployment can be gained through other broader based policies with less risk of encouraging lock-in. A carbon tax is broad based, but does not differentiate between technologies and thus may encourage lock-in of a newly introduced but inferior technology. A feed-in tariff differentiates between technologies to tailor support based on their stage of development, but can run the risk of accidentally excluding technologies.

There is no ideal policy that satisfies all the policy goals. However, for avoiding lock-in, reducing emissions, and ensuring that a superior technology is the one adopted in the long run, a hybrid policy of carbon tax and feed-in tariff is likely preferable. Small R&D and primary research subsidies can be funded sufficiently to gain a rough idea of a technology's progress ratio; this is largely accomplished already. A feed-in tariff can be established that provides different support to broad classes of technologies, with the support designed to take a technology close but not fully to breaking lock-in and achieving widespread adoption. Such policies are relatively inexpensive, as they target technologies early in their deployment. A broad carbon tax can provide the final support, thus gaining its "double dividend" and societal habit-changing benefits in achieving lower emissions.

Chapter 6

Discussion

6.1 Implications for Integrated Assessment Models

Many integrated assessment models have not taken into account endogenous technological change, let alone technological lock-in. As a result, models may have a much larger systematic uncertainty than is appreciated, particularly in their policy recommendations and estimates of optimal social costs of carbon. Lock-in may make transitions between technologies more difficult than expected, or alternatively cause sudden expected but beneficial shifts between technologies analogous to a phase change. Barring sudden transitions and even with deterministic progress ratios, the nature of lock-in and learning makes estimating when a technology will reach some desired price difficult as this is highly dependent on deployment, itself endogenously dependent on price. Policy can have unexpected effects, such as potentially altering which new technology is adopted even in favour of an inferior one. All of these conspire to make modelling an especially uncertain process.

Much of the focus on model uncertainty, such as with sensitivity analysis of parameters, is on precision. Accuracy is harder to establish, as it is more reliant on model assumptions and a lack of systematic errors. Ironically, Nordhaus illustrates this while trying to acknowledge the limitations of IAM models, when he notes that "analyses using integrated assessment economic models present an unrealistically smooth picture of the functioning of economic and political systems in much the same way that global climate models cannot capture the turbulence of weather systems."[Nordhaus, 2010]. Nordhaus is right that climate models present an unrealistically smooth picture, yet this is primarily an issue of precision, not accuracy; climate models are still accurate without resolving turbulence. Key is that small divergences can cause chaotic outcomes, that is outcomes extremely dependent on initial conditions. Turbulence does exhibit this, hence its unpredictability. Crucially however, the unpredictable nature of turbulence is irrelevant to climate model predictions. Climate models can be accurate without capturing the turbulence of weather.

In integrated assessment models, approximating technological change as an exogenous, or even simple endogenous process, also presents an unrealistically smooth process. Yet technological change and lock-in is fundamentally different. It is a detail that may itself cause substantially varying model outcomes which are not picked up by sensitivity analysis, or even different models all relying on a similar approach to technological change.

This is already demonstrated to some degree by the contrast between Nordhaus's conclusions of a benefit to delaying policy interventions, vs Acemoglu et al's finding that delaying action is costly, a conclusion robust to criticism of the choice of discount rate that plagued the Stern Review.[Acemoglu et al., 2012] Similarly, in a survey of IAM's including induced technological change, Edenhofer et al note that the way non fossil fuel technologies are modelled has a strong impact on abatement costs.[Edenhofer et al., 2006] Some integrated assessment models conduct sensitivity analysis of model parameters, drawing detailed policy recommendations. Such a detailed discussion of policy may be premature when these polices can have large impacts on innovation and the model results.[Pizer, 2002]

6.2 Uncertainty

In reality, the progress ratio is uncertain, especially among new technologies. Whether a technology will continue to improve at a given progress rate is also uncertain. Agents will have to make investment decisions without full knowledge of a technology's potential, though they will have an accurate idea of the current cost they have to pay. This complicates an agent's decision if they are choosing a technology they hope to also use in the future and which they would like to improve.

A retrospective examination of past energy forecasts, including the use of various types of electricity generation, has shown that "forecasters systematically underestimated uncertainties."[Craig et al., 2002] This unpredictability is both good and bad; some technologies, like nuclear, have unexpectedly climbed in cost while energy efficiency improvements have been much cheaper to implement than expected. Such an underestimation of the range of uncertainty in IAM's may already be occurring; in an essay published in PNAS on abatement goals and economic modelling, William Nordhaus mentions how "integrated assessment models are useful in making estimates of systemic uncertainty because they can incorporate all elements of the model and parameters" before adding several cautionary notes.[Nordhaus, 2010] Left out is any mention of the large uncertainties around technological change.

Uncertainty could effectively increase the distribution of preferences, resulting in more marginal technologies being deployed, as far sighted agents disagree on which technology will ultimately be best. Counteracting this, uncertainty can reduce an agent's desire to deploy expensive technologies without knowing if the investment will eventually pay off, reducing the strength of their ideological preferences and causing them to rely more on present cost. The uncertainty over a technology's potential is a reason to invest early in a wide variety of technologies in order to estimate their progress rate, and this is already what happens in much primary research and prototyping.

Uncertainty is beyond the scope of this essay, but would be an important addition to any integrated assessment models exploring the effects of lock-in. Without considering lock-in, the scope of what is possible and may be expected in the future of technological innovation may be too limited by current models, inaccurately constraining the discussion on how uncertain policy and the future is.

Chapter 7

Conclusion

Through an agent based model, this essay has demonstrated several ways in which policy interventions could have unexpected effects on the path of technological change. Such complexities and potential downsides need to be considered in designing policies and funding methodologies for science and industry R&D, as well as policies to spur changes in the path of technological innovation.

An agent-based model generating experience curves, based on the one in this essay, could be incorporated into a full integrated assessment model to elucidate if the models are robust to such an endogenous treatment of technological change. It may not be that a more sophisticated treatment of technological change reduces the uncertainty in integrated assessment models: it may well increase it. But without considering the complex dynamics of this important aspect of economic-climate modelling, it is difficult to accept detailed policy recommendations for guiding technological innovation.

By expanding the discussion of technological change and modelling, this essay can help reduce the systematic uncertainties that have plagued past energy technology forecasts, and improve the efforts taken to combat climate change.

Appendix A

MATLAB Code

A.1 Main body code

```
clear
disp('Start')
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Define agent preferences
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
numTech = 3; %Number of technologies to include in comparison.
numGroup = 4; %Defines how many 'groups' of agent types there are.

G1SD_array = [0.05, 0.05, 0.05]; %array of SD for different techs for Group 1
G2SD_array = [0.15, 0.05, 0.05]; %array of SD for different techs for Group 2
G3SD_array = [0.05, 0.05, 0.05]; %array of SD for different techs for Group 3
G4SD_array = [0.05, 0.05, 0.05]; %array of SD for different techs for Group 4
GSD_array = [G1SD_array;G2SD_array;G3SD_array;G4SD_array];
        %Concatenates arrays of SD.

G1Mean_array = [0,0,0]; %array of mean preferences for different techs
G2Mean_array = [0,0,0]; %array of mean preferences for different techs
G3Mean_array = [0,3,0]; %array of mean preferences for different techs
G4Mean_array = [0,0,3]; %array of mean preferences for different techs
GMean_array = [G1Mean_array;G2Mean_array;G3Mean_array;G4Mean_array];
        %Concatenates arrays of the mean.
preflength_array = [300,300,45,45];
        %Sets the number of agents for each group defined above
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Define technology parameters
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
subsidy = 0.2; %Level of Subsidy in decimal. So 0.1 is a 10% subsidy.

Co_arraytemp = [1.0,1.6,2.4]; %Initial cost at t=0 for each technology.
PR_arraytemp = [0.9,0.8,0.7]; %PR for each technology
D_arraytemp = [1000,20,10]; %Initial deployment at t=0 for each technology.
Q = 30.0; %The total amount to be deployed among all technologies by all agents.

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Use number of agents and details of the preference disribution to generate an
%array of the individual preferences for individual agents.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Inc = 0.03; %increment between preference values in preference array.
lbound = -3; %lower bound of preferences array
ubound = 3; %upper bound
Pref = []; %Initialize pref array.

%i is for agent group. It defines what mpreflength_array should be used.
%j is for technology number.

for i=1:numGroup; %Iterate over each group of agents
tempPref = []; %Temporary array of preferences holding one group of agents
for j=1:numTech %generate the array of preferences for each technology
    %functiongausspref_forV21 calls a function to generate the array of
    %preferences from a defined distribution (here gaussian) of
    %preferences. This returns an array mx of preference values, and an
    %array mz of preferences for agents. These arrays may not be the same
    %size.
    [mx,mz] = functiongausspref_forV21(lbound,ubound,Inc,GSD_array(i,j),
            GMean_array(i,j),preflength_array(i));
    mz = sort(mz); %sort the array of preferences before appending.
    tempPref = [tempPref,mz'];
            %Make a temporary array of preferences for a single technology
```

```
    %tempPref is for a given set of agents, over all technologies?
    %eval([genvarname(strcat('PrefTech',num2str(j)),who) ' = Anew'';']);
end
Pref = [Pref;tempPref];
        %Append arrays of preferences for each technology into one large array.
end

PrefDim = size(Pref); %Get the dimension of preferences
numDep = PrefDim(1); %Get the number of agents

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Years = [1:1:50]'; %Array of dates used, Typically 50 years.
Qdep = Q/numDep; %This determines how much is deployed by each agent

PR_array = PR_arraytemp(1:numTech);
        %truncate array to the correct number of technologies.
D_array = zeros(length(Years),numTech); %initialize deployment array.
D_array(1,:) = D_arraytemp(1:numTech); %Define and truncate deployment array.
alpha_array = log(PR_array)/log(2); %array of alpha values found from PR ratios
Co_array = Co_arraytemp(1:numTech); %truncate to the corrected number of technologies.

C_array(1,:) =  Co_array(1,:); %The initial cost in the cost array is Co.
C_arraystart = D_array(1,:).^alpha_array;
        %Record the initial cost for normalizing the array.
TotalCost(1,:) = 0*D_array(1,:); %The initial totalcost is 0

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%The array iterates over all years, excluding t = 0. Values at t=0 are set
%from the initial conditions.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

for t=2:length(Years) %Iterate over all years in the time array
    for i=1:numDep %iterate over each agent i and among technologies j
        eval = Pref(i,:) - C_array(t-1,:);
                %eval is the combination of preferences and costs agents decide among.
        maxtemp = max(eval);
```

```
                %find the maximum Pref-Cost combination among technologies.
        nummax = sum(eval == maxtemp);
                %how many technologes share this max preference?
        for j=1:length(eval)
                %iterate over each technology pref-cost combination.
            if eval(j) == maxtemp
                    %Find the technology(s) for the agent to deploy to.
                D_array(t,j) = D_array(t,j) + Qdep/nummax;
                        %Add the agents contribution to the technology
            end
        end
    end
    D_array(t,:) = D_array(t-1,:) + D_array(t,:);
            %add the deployment amount from this period to last periods deployment
    Q_array(t,:) = D_array(t,:) - D_array(t-1,:);
            %Calculate the amont deployed in this period
    Frac(t-1,:) = Q_array(t,:)/Q; %Find the fraction of deployment for each technology
    C_array(t,:) = (1./C_arraystart).*Co_array.*D_array(t,:).^alpha_array;
            %Calculate the new cost
    TotalCost(t,:) = C_array(t-1,:).*Q_array(t,:)*exp(-0.05*t); %The discounted cost.

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Implement the subsidy. The >= and <= specify the years for the subsidy.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    if t >= 10 & t <= 20
        C_array(t,1) = C_array(t,1)*(1+subsidy); %carbon tax
        %C_array(t,2) = C_array(t,2)*(1-subsidy); %subsidy of tech 2
        %C_array(t,3) = C_array(t,3)*(1-subsidy); %subsidy of tech 2
    end
end

%sum(sum(TotalCost)); %Find the total cost over all technologies.
%Emistemp = sum(TotalCost);
%Emis = Emistemp(1); %Cost of first technology
%Calculate cost Co at D=0 (extrapolating backwards to it)
Co_out = Co_array.*D_array(1,:).^(-alpha_array);
        %note the -alpha is to extrapolate backwards. alpha is itself negative
str = ['Co at D=0: ', num2str(Co_out)]; %Display Costs at D=0
```

```
disp(str)
to_out = D_array(1,:)./Q_array(2,:); %Display time backwards until D=0
str = ['t at D=0: ', num2str(to_out)];
disp(str)
Qo_out = Q_array(2,:); %Display the initial quantity deployed at t=0
str = ['Qo at t=0: ', num2str(Qo_out)];
disp(str)


%Assume Q is deployed in each time period all to one technology.
        %So total is Q*length(Years). Then the limit
%deployment is D_array + Q*length(Years), which is the best case scenario.
Co_limit = Co_array./(D_array(1,:).^alpha_array).*
        (D_array(1,:)+Q*length(Years)).^(alpha_array);
str = ['C limit: ', num2str(Co_limit)];
disp(str)
disp(C_array(50,:)) %Display the realized costs for comparison to the idealized Co_limit

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Define output figure properties
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
set(gcf,'DefaultLineLineWidth',1.5)
figure(1)
plot(Years,C_array)
axis([0 50 0 3])
set(gca,'FontSize',15)
xlabel('Time')
ylabel('Cost')
hleg1 = legend('PR = 0.9','PR = 0.8','PR = 0.7');
figure(2)
%loglog(D_array,C_array)
%plot(Frac)
subplot(1,3,1);
hist(Pref(:,1),mx)
axis([-3 3 0 150])/Users/Alastair/Documents/Tex/Economics/MA Essay/
        MA Essay v12 June 16.log
set(gca,'FontSize',15)
xlabel('Preferences')
```

```
ylabel('Number of agents')
subplot(1,3,2);
hist(Pref(:,2),mx)
%hleg1 = legend('PR = 0.9, Do = 100','PR = 0.7, Do = 10','Co = 0.4');
axis([-3 3 0 150])
set(gca,'FontSize',15)
xlabel('Preferences')
subplot(1,3,3);
hist(Pref(:,3),mx)
%hleg1 = legend('PR = 0.9, Do = 100','PR = 0.7, Do = 10','Co = 0.4');
axis([-3 3 0 150])
set(gca,'FontSize',15)
xlabel('Preferences')
```

A.2 Preference Distribution Subfunction

```
%This function will take in the distribution bounds, SD, mean, and number
%of requested preferences.
%It generates a distribution of these preference values.
function [x,z] = functiongausspref_forV13(lbound,ubound,Inc,SD,Mean,preflength)

x=lbound:Inc:ubound; %Array of preference values
y=gaussmf(x,[SD Mean]); %Gaussian distribution of preferences.

density = preflength/sum(abs(y)); %This is the density of preferences x at each y

for i=1:length(x)
        %iterate over each preference,
                %find the number of agents who have that preference value
   numval(i) = density*y(i);
end
clear i

numval = round(numval); %Round to an even number of agents
z = [];
for i=1:length(x)
    temparray = repmat(x(i), 1,numval(i));
            %creates a number of copies (numval) of the pref at a given x
```

```
    z = [z,temparray]; %append to one long array of preferences.
end

z = imresize(z, [1 preflength]);
        %Resize to the correct preflength number of preferences.
```

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