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Jennifer Morris[*†], Mort Webster[*] and John Reilly[*]

Abstract

Given that electricity generation investments are expected to operate for 40 or more years, the decisions we make today can have long-term impacts on the electricity system and the ability and cost of meeting long-term environmental goals. This research investigates socially optimal near-term electricity investment decisions under uncertainty in future technology costs and policy by formulating a computable general equilibrium (CGE) model of the U.S. as a two-stage stochastic dynamic program. The unique feature of the study is a stochastic formulation of technological learning. Most studies that include technological learning utilize deterministic learning curves in which a given amount of investment, production or capacity leads to a given cost reduction. In a stochastic framework, investment in a technology in the current period depends on uncertain learning that will result and lower future costs of the technology. Results under stochastic technological learning suggest that additional near-term investment relative to what is optimal under no learning can be justified at technological learning rates as low as 10–15%, and at the 20–25% rates commonly found in literature for advanced non-carbon technologies, significant additional near-term investment can be justified. We also find it can be socially optimal to invest more in non-carbon technology when the rate of learning is uncertain compared to the case where the learning rate is certain. Increasing marginal costs produce an asymmetric loss function that under uncertainty leads to more near-term non-carbon investment in attempt to avoid the situation of high non-carbon costs and an external economic environment that creates high demand for non-carbon technology.

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1. INTRODUCTION

Given that electricity generation investments are expected to operate for 40 or more years, the decisions we make today can have long-term impacts on the electricity system and the ability and cost of meeting long-term environmental goals. A key factor impacting optimal near-term investments is technological learning. If near-term investments can lower the future costs of non-carbon technologies (e.g. through learning-by-doing or scale effects), then there is greater incentive to make more non-carbon investments in the near-term. Studies of electricity investment decisions that include learning for technology costs are typically deterministic, most utilizing learning curves in which a given amount of investment or production or capacity leads to a given level of cost reduction (e.g. Kypreos and Bahn, 2003; van der Zwaan *et al.*, 2002; Messer, 1997; Loulou *et al.*, 2004; Seebregts *et al.*, 1999; Morris, 2002; Mattsson and Wene, 1997; Berglund and Soderholm, 2006; Kypreos and Barreto, 2000). However, here we advance the literature on technological learning by examining optimal investment in a stochastic framework where investment in the technologies changes the *probabilities* of future technology costs—i.e. the learning pay-off is uncertain. We do so by formulating a computable general equilibrium (CGE) model of the U.S. as a two-stage stochastic dynamic program.

We investigate socially optimal near-term electricity investment decisions that maximize expected economy-wide consumption given uncertainty in future technology costs and learning, as well as uncertainty in the future external economic environment that will affect demand for a technology. Here, we simulate this second uncertainty as a climate policy that impacts the demand for non-carbon technology by affecting the cost of conventional fossil technology through a carbon price. If a climate policy is implemented during the early- or mid-lifetime of a power plant, it greatly affects how cost-effective it is to run that plant and could even require the plant to shut down, which would undermine the case to build that plant in the first place. Even in the absence of policy, market forces alone also create uncertainty in the cost of conventional fossil generation and therefore uncertainty in the demand for non-carbon technology and the solvency and strategy of near-term investments. Such external economic uncertainty coupled with uncertainty in technology costs and technological learning, makes near-term decision-making quite difficult, suggesting the value of a formal decision-making under uncertainty approach.

In Section 2, we describe model and decision-making under uncertainty method, and describe the uncertainties in Section 3. Section 4 explores results under non-carbon cost uncertainty without technological learning. Section 5 then details the stochastic technological learning formulation, describes results with this learning formulation and explores sensitivity to the technological learning rate. We offer conclusions in Section 6.

2. THE MODEL

The problem we wish to consider is how the uncertain resolution of learning about a specific technology in the future affects investment decisions in that technology in the near term. Following a classic dynamic programming setup, we formulate the problem as a two-stage finite horizon problem, with uncertainty about technology costs and learning and the external economic environment resolved in the second period.

The DP objective is to choose actions to maximize total expected discounted social welfare in the economy over the planning horizon. In terms of the Stage 1 (near-term) decisions, the goal is to maximize current period consumption plus discounted expected future consumption. Utilizing the Bellman equation (Bellman, 1957) the objective function is:

$$V_t = max_{x_t}[C_t(S_t, x_t) + \gamma E\{V_{t+1}(S_{t+1}(S_t, x_t, \theta_t))\}] \quad (1)$$

where:

t is decision stage,
V is total value,
S is state (electric power capacity level of each technology and cumulative emissions level),
C is economy-wide consumption (welfare),
x is decision set (non-carbon share of new electricity and amount of emissions reductions),
θ is uncertainty set (probabilities assigned to Stage 2 non-carbon technology cost and Stage 2 policy)
γ is discount factor = (1 − discount rate). Discount rate = 4%.

In the DP, there is uncertainty (θ) in both the future cost of the non-carbon technology and the future economic environment (demonstrated in this work as the future emissions policy), as described in Section 3. Two decisions are made (so x_t in Equation 1 is a vector with two elements): (1) the non-carbon technology's share of new electricity in each stage (i.e. how much of the new capacity built should consist of non-carbon technologies?), and (2) Stage 1 reductions of electricity emissions (i.e. is it worth it to begin reducing emissions now in anticipation of future policy?).

A significant departure from previous work is that we represent these investment decisions within an economy-wide model because we believe feedbacks are important. We develop a single region computable general equilibrium (CGE) model approximating the U.S. in terms of overall size and composition of the economy that highlights choices between fossil and non-fossil electricity generation investment decisions. There is a single representative consumer that makes decisions about household consumption. There are six production sectors: crude oil, refined oil, coal, natural gas, electricity and other. Other, which includes transportation, industry, agriculture, services, etc., comprises the vast majority of the economy. The factors of production included are capital, labor and natural resources (crude oil, coal and natural gas). The base CGE model follows the structure of the MIT Economic Projection and Policy Analysis model (Chen *et al.*, 2016; Paltsev *et al.*, 2005), and is incorporated into the stochastic dynamic programming framework of Morris *et al.* (2014) and Morris (2013).

The underlying social accounting matrix (SAM) data is based on GTAP 5 (Hertel, 1997; Dimaranan and McDougall, 2002) data recalibrated to approximate 2010, which is used as the base year for the model. The model is written in General Algebraic Modeling System (GAMS) format and is formulated in MPSGE (Rutherford, 1999). Carbon dioxide (CO_2) emissions are associated with fossil fuel consumption in production and final demand.

Two electricity generation technologies are represented: conventional and non-carbon. There is a single conventional electric technology that uses coal and natural gas as its fuel.[1] The

[1] Conventional electricity aggregates all generation in the base year, including nuclear, hydro and other generation.

non-carbon electricity generation technology produces no carbon emissions and is more expensive, representing advanced non-carbon technologies like wind, solar, carbon capture and storage (CCS), and advanced nuclear. These technologies have little or no market penetration at present, but could take significant market share in the future under some energy price or climate policy conditions. The electricity produced from the generalized non-carbon technology is a perfect substitute for conventional electricity. It initially has a higher cost than conventional generation, which is set in the model by a markup, which is the cost relative to the conventional generation against which it competes in the base year. The base markup is set to 1.5, indicating that the non-carbon technology is 50% more expensive than conventional electricity. As the prices of inputs change endogenously over time, so too does the relative cost of the technologies.

The CGE model is dynamic, running from 2010 to 2030 in 5-year time steps. The processes that govern the evolution of the economy and its energy characteristics over time are: (1) capital accumulation, (2) fossil fuel resource depletion, (3) availability of non-carbon electricity technology, (4) population growth, and (5) energy efficiency improvements. The first three processes are endogenous while the last two are exogenous. Of particular importance for the uncertainty work is capital vintaging, which is applied to the electricity sector and reflects the irreversibility of decisions. Capital vintaging tracks the amount of electricity generation capacity available from previous years, remembering for each "vintage" (i.e. time period of installation) the technical features of the capacity (i.e. amount capital vs. labor vs. fuel, etc.).

This CGE model is then incorporated into the two-stage stochastic dynamic program (DP) to create the DP-CGE model. The deterministic CGE model is a myopic recursive–dynamic model that solves for each time period sequentially. For a given period, the original CGE model chooses an electricity technology mix (and all other outputs) based on the current-period maximization of consumption. However, here we are interested in the technology mix in each period that maximizes the current period consumption *plus* the expected future consumption, and so utilize the dynamic programming framework to take that into account.

The underlying CGE model continues to run in 5-year time steps, but the time horizon is divided into two decision stages for the DP. Stage 1 includes CGE periods 2015 and 2020 while Stage 2 includes 2025 and 2030 (and 2010 is the benchmark year). In each stage, the DP decisions are made for the two CGE periods included in that stage. In the underlying CGE model, the decision-maker is a hypothetical central planner of the economy. Although the optimal electricity mix is solved as if from the perspective of a central planner, one can think of it as the aggregate result of individual and identical firms maximizing their own profits according to their production functions, input costs and the policy constraints imposed by the central planner. The first decision about the non-carbon technology's share of new electricity in each stage is exogenously imposed on the CGE model to explore a wide range. The second decision to reduce Stage 1 emissions via a "self-imposed" emissions cap provides a price signal in the CGE model that affects the operation of existing electricity capacity as well as the optimal share of the non-carbon technology in new electricity. Including this second decision in the DP provides a price signal (the shadow price, i.e. carbon price, of the self-imposed emissions constraint) for the CGE model to endogenously react to by changing the operation of vintage capacity to reduce near-term emissions. Ultimately this emissions reduction decision variable affects choices of coal vs. natural gas, conventional vs. non-carbon, and building new vs. altering the operation of existing capacity.

The DP-CGE model is solved in two steps. First, the CGE model is run for each stage for each possible scenario (each combination of decision and uncertainty realization), calculating the total consumption for each stage. The decisions and uncertainty realizations are exogenously imposed on the CGE model, which then endogenously chooses all other output quantities, including the shares of natural gas and coal generation. Second, backward induction is performed by the DP using the consumption values for each stage and the probabilities of the uncertainty realizations. The DP follows the classic act-then-learn framework: Stage 1 decisions are made under uncertainty in technology cost and policy, which are revealed before the Stage 2 decision is made. In effect, the CGE model performs intraperiod optimization and the DP performs interperiod optimization.

3. UNCERTAINTIES

Market demand for non-carbon technology is determined by both its internal cost and how the external economic environment affects costs of competing fossil technologies. Uncertainty in both of these factors is explored. Within the CGE model, the decision of which technologies to build is driven by the relative costs of the technologies. As mentioned previously, the cost of the non-carbon technology is initially set in the model by a markup, which is the cost relative to the conventional fossil generation against which it competes. The markup is initially set to 1.5, indicating that the non-carbon technology is 50% more expensive than conventional fossil electricity in the base year of the model. To model uncertainty in the Stage 2 cost of the non-carbon technology, the markup is also set at the beginning of Stage 2 and its value made uncertain. Any change in the markup from Stage 1 to Stage 2 is driven by the cost of the non-carbon technology, as the cost of the base conventional generation is held constant for the markup calculation. The DP-CGE model uses a discrete approximation of the continuous uncertainty in future cost of the non-carbon technology. Specifically, a discrete three-point distribution is assumed with three non-carbon technology cost scenarios: (1) a markup of 1: non-carbon generation costs the same as conventional generation (MU1); (2) a markup of 1.5: the non-carbon generation continues to cost 50% more than conventional generation (MU1.5); and (3) a markup of 3: the non-carbon generation costs triple conventional generation (MU3). These markup values are informed by recent studies that have conducted expert elicitations of the costs of advanced generation technologies. These studies elicit technology costs for 2030 (which can be used for the Stage 2 markup in the DP-CGE model). Looking at the cumulative probability distribution for CCS capital costs from Chan *et al*. (2010), we can estimate the 5th, 50th and 95th percentiles. Putting the capital costs numbers into an LCOE calculation (Morris et. al 2010) provides markup values for those percentiles. The 5th, 50th and 95th percentile markups are 1.06, 1.63, and 2.82. Baker *et al.* (2009) also provides a combined probability distribution of the expert elicitations for CCS. Markups estimated from figures in that paper are 1.075, 1.35, and 1.45 for the 5th, 50th and 95th percentile. For other studies that do not provide a cumulative probability distribution, we can look at the probability range of expert judgments and translate into markups using the Morris et al. (2010) LCOE calculation. For nuclear, estimating values from Anadon *et al.* (2012) gives markups ranging from 0.68 to 4.01. For solar, estimating values Bosetti *et al.* (2012) gives markups of 0.67 to 4.18.

With these studies in mind (summarized in **Table 1**), it is assumed that markups of 1, 1.5 and 3 are reasonable approximations for the 5th, 50th and 95th percentiles for the cost of the generalized non-carbon technology for this model. Using the extended Pearson-Tukey discrete approximation method (Keefer and Bodily, 1983), the base probabilities of high (MU3), medium (MU1.5) and low (MU1) outcomes are assigned to be 0.185, 0.63, and 0.185 respectively. Additional mean-preserving probability spreads are also explored. In Section 5, stochastic technological learning is then incorporated by having the Stage 1 non-carbon generation shares determine the probabilities of the Stage 2 non-carbon technology cost scenarios.

At the same time that the cost of non-carbon technology is uncertain, the external economic environment causes the cost of competing fossil technologies to be uncertain as well, which in term creates uncertainty in the demand for non-carbon technology. Here we simulate this external uncertainty as a climate policy that impacts the demand for non-carbon technology by affecting the cost of conventional fossil technology through a carbon price. Uncertain fossil fuel prices, fossil resources, fossil extraction technology, other regulations affecting fossil technology, and other factors create to differing degrees the same external uncertainty we demonstrate with a climate policy. We make the Stage 2 emissions policy uncertain. The potential policies are defined as caps on the cumulative emissions from the electric power sector from 2015 to 2030. A discrete three-point probability distribution with three policy scenarios is assumed: (1) no policy; (2) an emissions cap of 20% below cumulative no policy emissions (−20% Cap); and (3) an emissions cap of 40% below cumulative no policy emissions (−40% Cap). In order to focus on technology cost and learning uncertainty, for this paper each policy is assumed to be equally likely and assigned a probability of 1/3 (for a deeper exploration of policy uncertainty, see Morris *et al.*, 2014).

Table 1. Markups derived from expert elicitation studies.

	CCS (Chan *et al.,* 2010)	**CCS** (Baker *et al.,* 2009)	**Solar** (Bosetti *et al.,* 2012)	**Nuclear** (Anadon *et al.,* 2012)
5th percentile OR Min	1.06	1.075	0.67	0.68
50th percentile	1.63	1.35		
95th percentile OR Max	2.82	1.45	4.18	4.01

Note: The percentiles apply to both CCS estimates while the Min and Max apply to solar and nuclear.

Table 2. Uncertain non-carbon cost scenarios.

	Probability of Stage 2 Markup				
Scenario	**1**	**1.5**	**3**	**Expected Markup**	**Variance**
MU uncert 1	0.058	0.800	0.143	1.69	0.335
MU uncert 2	0.185	0.630	0.185	1.69	0.463
MU uncert 3	0.328	0.440	0.233	1.69	0.560
MU uncert 4	0.328	0.440	0.233	1.69	0.605
MU uncert 5	0.403	0.340	0.258	1.69	0.680

4. RESULTS UNDER NON-CARBON COST UNCERTAINTY WITHOUT TECHNOLOGICAL LEARNING

First we explore the impact of uncertainty in the cost of the non-carbon technology without technological learning. Four policy scenarios are considered: (1) certain −40% cap, (2) certain −20% cap, (3) certain no policy, and (4) uncertain policy in which each policy is assumed to be equally likely (1/3 probability each)[2]. For each of these four policy scenarios, eight non-carbon cost scenarios are considered. The first three scenarios assume that the Stage 2 non-carbon cost—the markup (MU)—is known with certainty to either be 3, 1.5, or 1. The remaining five non-carbon cost scenarios assume uncertainty in the markup at different mean-preserving spreads (see **Table 2**). Each of these five scenarios result in the same expected markup (e.g. preserve the mean of the distribution), but different variances. In this way, we can isolate the effect of greater uncertainty, distinct from the effects of higher or lower average costs.

In the results of this section, the Stage 2 cost of the non-carbon technology and the Stage 2 policy (external economic environment) affect Stage 1 decisions through two main avenues. First, they influence the amount of non-carbon technology desired in Stage 2, which may be constrained if the non-carbon growth rate from Stage 1 to Stage 2 is limited. In this work we assume that the maximum rate of non-carbon growth between stages allows the share of non-carbon in new investment to increase by no more than 50 percentage points from Stage 1 to Stage 2 (for example, if 20% of investment is in the non-carbon technology in Stage 1, then the max non-carbon share in Stage 2 is 70%). If the non-carbon technology will be lower cost in Stage 2, more non-carbon investment in Stage 1 is desirable because it will allow a greater share in Stage 2. This increased non-carbon investment could lead to lower Stage 1 emissions, even though otherwise it would be desirable to emit more in Stage 1 and less in Stage 2 when it is less costly to do so. Second, the uncertainty factors affect the costs of emissions reductions in Stage 2, which in turn affects the optimal level of action in Stage 1. If it is going to be costly to reduce emissions in Stage 2 because the cost of non-carbon generation is high, then it will be desirable to reduce more emissions in Stage 1 in order to reduce the Stage 2 emissions reduction burden. On the other hand, if the cost to reduce emissions in Stage 2 is going to be low because non-carbon generation is low cost, then fewer reductions need to be pursued in Stage 1.

Table 3 shows the optimal Stage 1 electricity investment and emissions reduction strategies under the different non-carbon cost scenarios and policy scenarios. In all cases, new electricity investments are responsible for approximately 40% of all generation. These results are explored in the following sections.

4.1 Deterministic Non-Carbon Technology Cost

First, let us focus on the scenarios when the non-carbon cost is known with certainty and is either higher (MU3) or lower (MU1) than the base assumption of 1.5. In order to meet the stringent

[2] The case in which there is a 1/3 probability of each policy is used to illustrate the impact of policy uncertainty. One should bear in mind that is just one example and that different assumptions about the probability distribution will impact results, as demonstrated in Morris *et al.* (2015).

Table 3. Optimal Stage 1 strategies under non-carbon cost and policy scenarios.

Policy Scenario	Stage 1 Decision		Markup Scenario: Certain MU3	Certain MU1.5	Certain MU1	MU uncert 1	MU uncert 2	MU uncert 3	MU uncert 4	MU uncert 5
Certain –40% Cap	**Share of New Investment**	Non-carbon	15%	35%	65%	35%	35%	35%	35%	35%
		Gas	78%	51%	18%	51%	51%	51%	51%	51%
		Coal	7%	14%	17%	14%	14%	14%	14%	14%
	Reductions	*Emissions*	*-35%*	*-24%*	*-16%*	*-24%*	*-24%*	*-24%*	*-24%*	*-24%*
Certain –20% Cap	**Share of New Investment**	Non-carbon	0%	5%	45%	5%	5%	0%	0%	0%
		Gas	82%	65%	30%	65%	65%	82%	82%	82%
		Coal	18%	30%	25%	30%	30%	18%	18%	18%
	Reductions	*Emissions*	*-13%*	*-6%*	*-9%*	*-6%*	*-6%*	*-13%*	*-13%*	*-13%*
Certain No Policy	**Share of New Investment**	Non-carbon	0%	0%	45%	0%	0%	0%	0%	0%
		Gas	63%	63%	30%	63%	63%	63%	63%	63%
		Coal	37%	37%	25%	37%	37%	37%	37%	37%
	Reductions	*Emissions*	*0%*	*0%*	*-9%*	*0%*	*0%*	*0%*	*0%*	*0%*
Policy Uncertainty *(1/3 Probability Each Policy)*	**Share of New Investment**	Non-carbon	5%	20%	55%	20%	20%	15%	15%	15%
		Gas	7%	17%	21%	17%	17%	15%	15%	15%
		Coal	88%	63%	24%	63%	63%	70%	70%	70%
	Reductions	*Emissions*	*-24%*	*-18%*	*-11%*	*-18%*	*-18%*	*-18%*	*-18%*	*-18%*

Note: The MU uncert scenarios are defined in 2. They all have the same mean and are ordered by increasing variance (i.e. higher probabilities of the low and high cost outcomes). MU uncert 2 uses the base Pearson-Tukey probabilities.

−40% cap when the non-carbon technology is expensive (MU 3), it is best to rely on natural gas and to consume less electricity overall due to the high prices of electricity (since both non-carbon and conventional generation are expensive). In that case, in Stage 1 it will be optimal to invest in 15% non-carbon, 78% natural gas and 7% coal generation and reduce emissions by 35% below reference. Significant Stage 1 emissions reductions are optimal in this case because emissions reductions are more costly in Stage 2 due to the high non-carbon cost. Therefore, lower Stage 1 emissions ease the burden of reducing emissions in Stage 2. When the markup is 1.5, the optimal Stage 1 decision is a new electricity investment mix of 35% non-carbon, 51% natural gas and 14% coal and emissions reductions of 24%. When the markup is 1, more non-carbon investment is optimal in Stage 1—65% non-carbon, 18% natural gas and 17% coal, and 16% emissions reductions. Fewer Stage 1 emissions reductions are required in this case since emissions can be easily reduced in Stage 2 by using an abundance of low-cost non-carbon generation, which will not be limited in growth because sufficient investment was made in Stage 1.

In the −20% cap and no cap scenarios, a markup of 3 leads to no non-carbon investment and a markup of 1 leads to 45% non-carbon investment in Stage 1. Even when there is no policy, if the Stage 2 markup is 1 it is optimal to make significant investments in non-carbon generation in Stage 1 to enable further expansion in Stage 2. Relying more on low-cost non-carbon electricity in Stage 2 frees up coal and natural gas resources for use in other sectors at a lower price (since the demand for these resources from the electricity sector decreases).

In the uncertain policy scenario, defined here as 1/3 probability of each policy, when the markup is 3 the optimal Stage 1 investment in non-carbon is 5%, in contrast to 15% under the −40% cap case and 0% under the other policy cases. Similarly, the optimal Stage 1 emissions reductions are 24%, in contrast to 35% reduction under the −40% cap and 13% reduction under the −20% cap. This hedging strategy protects against the particularly high risk associated with there being a −40% cap and a markup of 3, which would make it very expensive in Stage 2 to meet the cap (if enforced) due to costly or uneconomical non-carbon generation. The 24% emissions reduction hedge in Stage 1 helps to ease the burden of expensive emissions reductions in Stage 2 that may be required depending on the policy ultimately implemented. When the markup is 1.5, the optimal Stage 1 decision is an electricity mix of 20% non-carbon, 63% natural gas and 17% coal and emissions reductions of 18%. When the markup is 1, the optimal Stage 1 strategy is 55% non-carbon, 24% natural gas and 21% coal and 11% emissions reductions. In that case, Stage 1 non-carbon investment has value regardless of the policy that is ultimately implemented because it allows non-carbon investment to grow without limit in Stage 2 if it turns out to be low-cost. Fewer Stage 1 emissions reductions are required in that case since emissions can be easily reduced in Stage 2 by using an abundance of low-cost non-carbon.

4.2 Uncertain Non-Carbon Technology Cost

Next, let us consider the scenarios in which the non-carbon cost is uncertain (also in Table 3). If it is certain there will be a −40% cap or certain there will be no cap, non-carbon cost uncertainty does not affect the optimal Stage 1 strategy. For a wide range of distributions with different variances, the strategy is the same as when the markup is 1.5 with certainty. Similarly, if it is known that there will be a −20% cap or if the policy is uncertain with 1/3 probability each, lower variance distributions (MU uncert 1, 2) result in the same strategy as when the markup is known to be 1.5. However, the higher variance probability distributions of cost (MU uncert 3, 4, 5) result in less non-carbon—0% (instead of 5%) in the −20% cap case and 15% (instead of 20%) in the uncertain policy case. In these cases, the probability that the markup is 3 is too high to warrant as much investment in non-carbon in Stage 1. It is a safer bet to invest in less non-carbon in Stage 1 (since using non-carbon in Stage 2 many not be reasonable depending on the realized cost).

These results show very weak or no impact from uncertainty in the non-carbon cost on the optimal Stage 1 strategy. Most cases with non-carbon cost uncertainty result in the same strategy as the strategy when a 1.5 markup is certain (i.e. the "middle" strategy). There are some instances when that is not the case and the non-carbon cost uncertainty results in less non-carbon investment in Stage 1 than the "middle" strategy, but only 5% less. Other probability distributions for the non-carbon cost markup that are not mean-preserving may impact the Stage 1 strategy, but this would be caused in part by the higher or lower expected costs. Ultimately, the effect of non-carbon cost uncertainty, in terms of the causal mechanisms discussed here, is small.

5. RESULTS UNDER NON-CARBON COST UNCERTAINTY WITH STOCHASTIC TECHNOLOGICAL LEARNING

The previous section showed that, without technological learning, uncertainty in the non-carbon cost has a very weak effect on the Stage 1 optimal decisions, given the experimental design explored. There is, however, another potential mechanism through which such uncertainty can have an impact: learning-by-doing and scale effects can alter the value of near-term investment by accounting for additional benefits. If there is technological learning, such that the expected future cost of the technology decreases as the amount of near-term investment in that technology increases, then near-term investments could reduce future costs, providing greater flexibility and ease in meeting future policy. In this section, we explore how the inclusion of technological learning, in a stochastic setting, influences near-term optimal investment decisions.

Specifically, we explore the following question: how does the optimal Stage 1 strategy change when the amount of non-carbon investment in Stage 1 affects the probabilities of the non-carbon cost markup in Stage 2? In contrast to the deterministic learning curves commonly found in the literature, here we investigate technological learning in a stochastic framework in which a given amount of capacity investment changes the *probabilities* of future technology costs.

5.1 Stochastic Technological Learning Formulation

The representation of stochastic technological learning in the model is informed by learning-by-doing (LBD) curves (also known as experience curves), which represent how the cost of a technology declines as a function of cumulative production or capacity. For electricity generation technologies, LBD curves are often developed for categories of technologies based on cumulative installed capacity (Clarke *et al.*, 2008). LBD formulations are founded upon the concept that technology improves and costs decline as cumulative experience with the technology increases and repetition and familiarity leads to greater efficiency. Empirical research using data on cumulative installed capacities and technology costs has been used to develop learning curves for electricity technologies (e.g., Ibenholt, 2002; Colpier and Cornland, 2002; Yeh and Rubin, 2007). Such studies can be used in this work to calibrate the technological learning parameters to reflect the empirical relationship between cumulative installed capacity and technology cost reductions.

In the LBD literature, LBD curves are often expressed as power functions, for example:

$$C_q = C_0 * q^{-b} \tag{2}$$

where C_q is the cost per unit q, C_0 is the cost for the first unit, q is the cumulative capacity or production (experience over time) and b is a so-called experience index. The value 2^{-b} is called the progress ratio (PR). If an experience curve shows a progress ratio of 85 percent it means that cost declines by 15 percent for each doubling of cumulative capacity. Some studies use the term learning rate (LR), defined as (100-PR). Studies show that progress ratios vary significantly across technologies. For energy technologies, studies have shown that the progress ratio varies from 80 to more than 100 percent[3] (Neij, 1997).

Here, we propose a model of stochastic technological learning in which the Stage 1 non-carbon shares affect the probabilities of the Stage 2 non-carbon cost scenarios. For the three-point discrete distributions used here, the model is parameterized so that as the amount of Stage 1 non-carbon increases, the probability of a low Stage 2 markup (P_0^L) increases, and the probability of a high Stage 2 markup (P_0^H) decreases. Specifically,

$$P\{MU=1\} = P_0^L + BS_1 * \pi^L \tag{3}$$

$$P\{MU=3\} = P_0^H + BS_1 * \pi^H \tag{4}$$

$$P\{MU=1.5\} = 1 - P\{MU=1\} - P\{MU=3\} \tag{5}$$

where BS_1 represents the Stage 1 non-carbon share, which corresponds to a cumulative non-carbon capacity at the end of Stage 1. For a starting distribution, using the extended Pearson-Tukey method, P_0^L and P_0^H are 0.185. The values of the technological learning parameters π^L and π^H can then be calibrated to be consistent with the LBD literature.

Calibration requires several informational components: technology cost in 2010, capacity in 2010 and 2020, and a progress ratio. Because the model defines the cost of the non-carbon technology in terms of a markup over the conventional technology, those informational components are required for both a conventional and a non-carbon technology. For our calculations we use natural gas generation for the conventional technology and renewables for the non-carbon technology. Natural gas is assigned a progress ratio (PR) of 90% (consistent with e.g. Colpier and Cornland, 2002; McDonald and Schrattenholzer, 2001) and renewables are assigned a PR of 80% (consistent with e.g. Ibenholt, 2002; van der Zwaan and Rabl, 2003;

[3] A progress ratio of over 100% reflects costs increasing despite growing capacity, and is typically explained by improvements made in areas such as performance, efficiency, safety, etc.

McDonald and Schrattenholzer, 2001). 2010 capacity and projected 2020 capacity for gas and renewable generation are from EIA (2013). 2010 costs for gas and renewables are defined as the levelized cost of electricity (LCOE), which is the price of electricity per kWh taking into account capital, operating, fuel, and other costs. LCOE for renewables is set such that the markup of renewables over gas is 1.69, matching the expected markup using the base Pearson-Tukey probabilities. The LCOE for 2020 for gas and renewables is then calculated—using the learning curve, not the model.[4] Based on the amount of capacity added since 2010 and the progress ratio, the 2020 LCOE is reduced compared to the 2010 LCOE.

Figure 1 shows the change in costs for the technologies that result from this simple learning curve calculation. More renewable capacity is expected to be added during that time period than natural gas capacity and renewables also have a higher learning rate (20% vs. 10%), which results in the renewable cost decreasing by 6.2% and the natural gas cost decreasing by 1.6%. Typical LBD studies focus on the cost reduction of a single technology (e.g., line A in Figure 1), but here we are focused on the reduction in the cost of the non-carbon technology relative to the cost of conventional generation. Dividing the 2010 cost for renewables by the 2010 cost for natural gas yields the markup of 1.69. Dividing the 2020 projected cost for renewables by the 2020 projected cost for natural gas yields a markup of 1.61, representing a 4.5% decrease in the relative cost of the non-carbon technology from 2010 to 2020.

The change in the markup from 1.69 to 1.61 corresponds to renewable generation capacity increasing from 126 gigawatts (GW) to 154 GW. In the DP-CGE model, different Stage 1 non-carbon investment decisions will result in different levels of cumulative non-carbon capacity

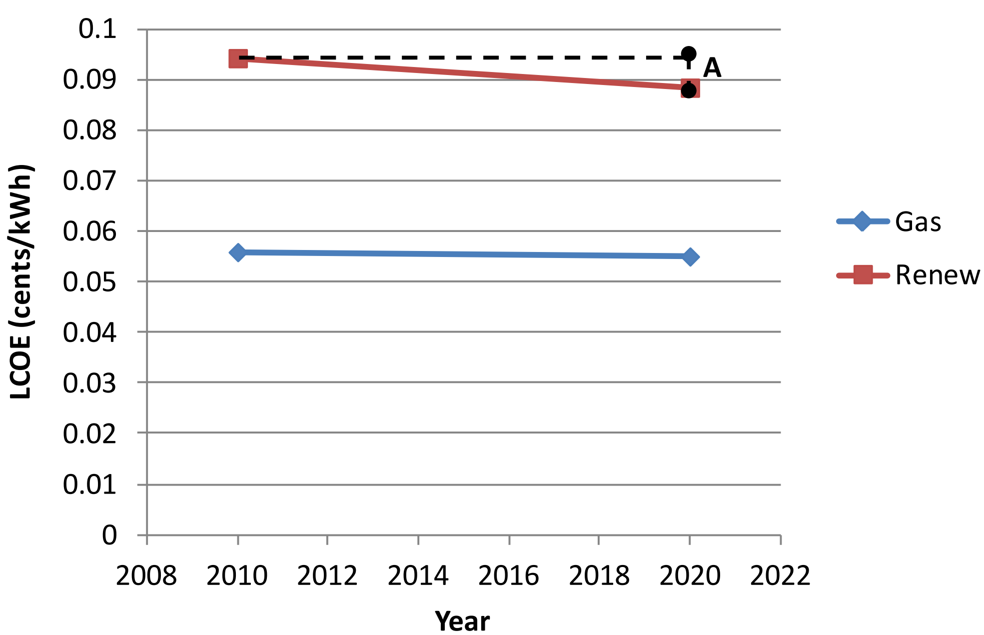

Figure 1. Changing costs of technologies using learning curve.

[4] This learning curve approach does not explicitly account for changing input prices over time (e.g. fuel, capital, labor, etc.).

at the end of Stage 1. For example, a 25% share of non-carbon in Stage 1 investment corresponds to approximately 155 GW of capacity in 2020. Since the base Pearson-Tukey probabilities and zero non-carbon investment in Stage 1 result in an expected markup of 1.69, 25% non-carbon investment in Stage 1 should be calibrated to result in markup probabilities that have an expected markup of 1.61. So the technological learning parameters (π^L and π^H) should be set such that the expected markup when you chose 25% non-carbon in Stage 1 is 1.61. A set of parameter values that achieve this are $\pi^L = 0.3$ and $\pi^H = 0.1$. The resulting model of stochastic technological learning is illustrated in **Table 4** using representative Stage 1 investment decisions. Less non-carbon investment in Stage 1 leads to higher probabilities of MU3 while more non-carbon investment in Stage 1 leads to higher probabilities of MU1.

In the DP-CGE model, Stage 1 decisions about electricity technologies and emission reductions must be made without knowing which of the three non-carbon costs will be realized in Stage 2, but rather with expectations about which costs are most likely and an understanding that the cost will be driven by near-term investments in non-carbon generation.

Table 4. Stochastic technological learning: probability of Stage 2 non-carbon cost markup given Stage 1 non-carbon share.

	Stage 2 Non-Carbon Cost Markup			
Stage 1 Non-carbon Share	**1**	**1.5**	**3**	**Expected Markup**
0%	0.185	0.630	0.185	1.69
5%	0.198	0.623	0.180	1.67
10%	0.210	0.615	0.175	1.66
15%	0.223	0.608	0.170	1.64
20%	0.235	0.600	0.165	1.63
25%	0.248	0.593	0.160	1.61
30%	0.260	0.585	0.155	1.60
35%	0.273	0.578	0.150	1.58
40%	0.285	0.570	0.145	1.57
45%	0.298	0.563	0.140	1.55
50%	0.310	0.555	0.135	1.54
55%	0.323	0.548	0.130	1.52
60%	0.335	0.540	0.125	1.51
65%	0.348	0.533	0.120	1.49
70%	0.360	0.525	0.115	1.48
75%	0.373	0.518	0.110	1.46
80%	0.385	0.510	0.105	1.45
85%	0.398	0.503	0.100	1.43
90%	0.410	0.495	0.095	1.42
95%	0.423	0.488	0.090	1.40
100%	0.435	0.48	0.085	1.39

5.2 Results with Stochastic Technological Learning

Table 5 shows the optimal Stage 1 strategies for four policy scenarios when technological learning is modeled, along with the optimal strategies from the previous section without technological learning or cost uncertainty. In the table, the expected markup for the technological learning cases can be used to identify the effective probabilities for the markups in Table 4. The inclusion of technological learning does not change the Stage 1 strategy for the deterministic policies of −20% cap or no cap. However, if a −40% cap is known with certainty or if the policy is uncertain with each policy equally likely, technological learning drastically changes the strategy. For the deterministic −40% cap scenario, a 95% non-carbon share and a 19% emissions reduction are optimal in Stage 1 (vs. 35% non-carbon and 24% emissions reductions in the absence of technological learning). When the policy is uncertain, a 65% non-carbon share and a 20% emissions reduction are optimal (vs. 20% non-carbon and 18% emissions reductions in the absence of technological learning). In these cases, the incremental cost of more non-carbon investment in Stage 1 is offset by the additional benefit of reducing the probability of having a markup of 3 under a −40% cap policy, which would be very costly (if enforced).

Table 5. Optimal Stage 1 strategies with stochastic technological learning for the non-carbon technology.

	Expected Markup (MU)	Share of New Investment			Emissions Reductions
		Non-Carbon	Coal	Gas	
Certain −40% Cap					
Certain MU3	3.00	15%	7%	78%	-35%
Certain MU1.5	1.50	35%	14%	51%	-24%
Certain MU1	1.00	65%	17%	18%	-16%
Uncert MU No Learn*	1.69	35%	14%	51%	-24%
Uncert MU Learn	1.40	95%	3%	2%	-19%
Certain −20% Cap					
Certain MU3	3.00	0%	18%	82%	-13%
Certain MU1.5	1.50	5%	30%	65%	-6%
Certain MU1	1.00	45%	25%	30%	-9%
Uncert MU No Learn*	1.69	5%	30%	65%	-6%
Uncert MU Learn	1.67	5%	30%	65%	-6%
Certain No Policy					
Certain MU3	3.00	0%	37%	63%	0%
Certain MU1.5	1.50	0%	37%	63%	0%
Certain MU1	1.00	45%	25%	30%	-9%
Uncert MU No Learn*	1.69	0%	37%	63%	0%
Uncert MU Learn	1.69	0%	37%	63%	0%
Policy Uncertainty (1/3 Each Policy)					
Certain MU3	3.00	5%	7%	88%	-24%
Certain MU1.5	1.50	20%	17%	63%	-18%
Certain MU1	1.00	55%	21%	24%	-11%
Uncert MU No Learn*	1.69	20%	17%	63%	-18%
Uncert MU Learn	1.49	65%	18%	17%	-20%

Note: Uncert MU No Learn assumes base Pearson-Tukey probabilities and corresponds to the MU uncert 2 case in Table 2.

In both the −40% cap and uncertain policy cases, the strategy with technological learning involves more non-carbon investment than when it is known for certain that the markup will be 1 (95% vs. 65% for −40% cap and 65% vs. 55% for policy uncertainty). With the stochastic technological learning, the justification for the additional Stage 1 non-carbon investment is to bring the expected non-carbon cost down for Stage 2. You would not make the additional investments if you were certain the cost would be low regardless of actions. In other words, if low future costs are "free", you do not need to do as much in Stage 1. However, if you can pay to increase the probability of low future costs by investing more now, it may be worth it to do so. Lower future costs provide greater flexibility and ease in meeting future policy. This flexibility is particularly valuable as the probability of a stringent emissions cap increases.

Similarly, if technological learning is deterministic, less non-carbon investment is optimal in Stage 1. Under deterministic technological learning, near-term investments determine the actual future markup instead of the probabilities of future markups. Deterministic technological learning is modeled by taking the expected markups from the stochastic technological learning formulation (Table 4) and assuming that markup value occurs with certainty if the necessary amount of Stage 1 investment is made. For the uncertain policy case, the optimal decision with deterministic technological learning is 25% non-carbon investment, lower than the 65% that is optimal with stochastic technological learning. If you know exactly how your investments will reduce future costs, you will only invest the minimum amount needed to achieve the desired cost reduction. In the stochastic case, you do not know how effective your investments will be at reducing future costs, and you have incentive to invest more in order to increase the chances of a low-cost outcome. This is true because increasing marginal costs produce an asymmetric loss function such that one should try to avoid the situation of high non-carbon costs and an external economic environment that creates high demand for non-carbon technology (e.g. a stringent emissions cap). With uncertain learning, more near-term non-carbon investment is the best way to lower the probability of ending up in that particularly undesirable situation.

Ultimately, whether or not more near-term investment is justified depends on expectations about the non-carbon cost distribution, which is determined by the technological learning parameters, as well as the expected future economic environment (e.g. future policy). Balancing these expectations provides the optimal hedge strategy.

5.3 Sensitivity to Stochastic Technological Learning Rate

In this section sensitivity analysis is conducted on the technological learning parameters π^L and π^H in order to further explore the impact of technological learning on the results. The parameters π^L and π^H determine the probabilities of the markups that result from different Stage 1 non-carbon decisions (see equations 3–5). These two parameters determine the magnitude of the technological learning—higher values lead to larger impacts on the probabilities and larger reductions in the expected markup for a given Stage 1 non-carbon decision.

The magnitude of the technological learning can be translated to learning rates (i.e. the percent reduction in cost for each doubling of cumulative capacity). The base technological learning parameters used in the previous section (π^L = 0.3 and π^H = 0.1) were calibrated to learning-by-doing literature estimates of learning rates of 20% for non-carbon generation and10% for conventional generation. In the same manner, we can identify technological learning parameters that correspond to different learning rates for the non-carbon technology (holding the conventional generation learning rate at 10%). **Table 6** illustrates values of parameters π^L and π^H that correspond to learning rates covering the typical range in the literature.[5] The higher the learning rate, the more expected costs are reduced.

Using these parameter values we can explore how different learning rates affect the optimal Stage 1 decisions. First, consider the scenario when policy is known for certain to be a −40% cap (**Figure 2**). The 0% learning rate is equivalent to no technological learning—the cost stays constant regardless of the non-carbon investment in Stage 1. As the learning rate increases, more non-carbon is optimal in Stage 1. This is because with higher learning rates, Stage 1 non-carbon investments are more valuable as they have larger impacts on the probabilities of future markups and result in larger reductions in the expected markup. Essentially, higher technological learning rates mean you get "more bang for your buck" of non-carbon investment in Stage 1, and therefore there is incentive to invest more in non-carbon generation. With high enough technological learning rates (20–30%), the optimal share of non-carbon in Stage 1 increases to 95%, which makes the probability of MU=1 very high (47–73%), and the probability of MU=3 very low (1.4%–9%). The same effect, though weaker, is seen when the policy is uncertain (defined here as 1/3 probability of each policy) (**Figure 3**).

For a −40% cap, the optimal Stage 1 non-carbon share differs from the strategy without technological learning at a learning rate of 10%. A learning rate of 15% leads to a different decision when the policy is uncertain. Both of these rates are lower than most estimates from the literature of learning rates for advanced non-carbon technologies, which typically fall around 20–25%. At those learning rates, technological learning has a significant impact on the optimal Stage 1 non-carbon share under these two policy scenarios.

Under a −20% cap, a learning rate of at least 25% is required to change the optimal Stage 1 non-carbon share, which jumps from 5% to 95%. With a 25% learning rate, 95% non-carbon

Table 6. Technological learning parameters and learning rates (LR).

π^L	π^H	*LR*
0.000	0.000	0%
0.001	0.001	5%
0.050	0.050	10%
0.100	0.100	15%
0.300	0.100	20%
0.540	0.100	25%
0.575	0.180	30%

[5] There are other sets of parameter values that result in different probability distributions, but the same expected markup and therefore the same learning rates. The parameter values in Table 6 are therefore examples of values that correspond to a set of learning rates.

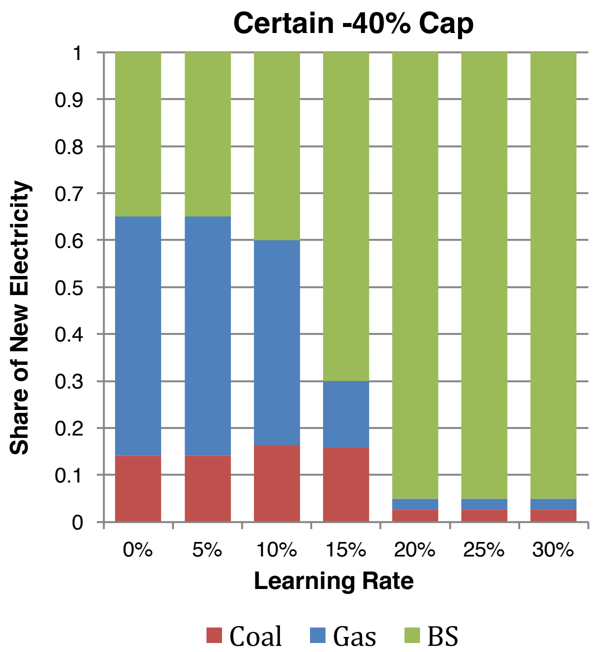

Figure 2. Stage 1 shares of new electricity under a –40% Cap with different learning rates.

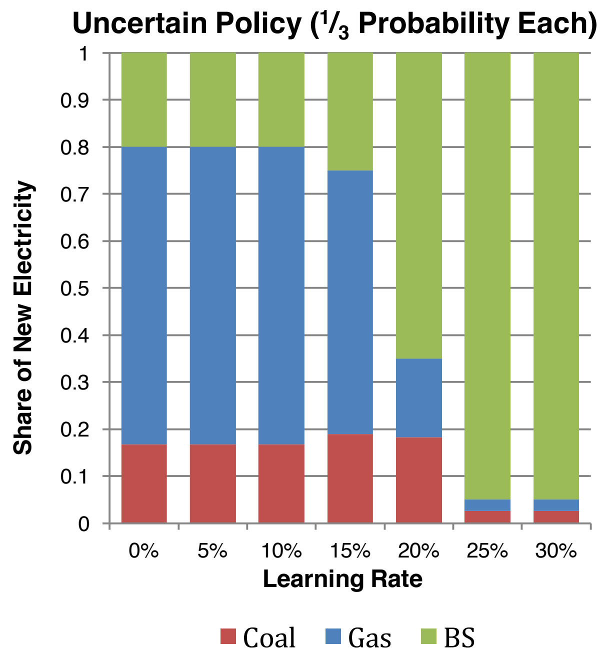

Figure 3. Stage 1 shares of new electricity under policy uncertainty (1/3 probability each policy) with different learning rates.

investment in Stage 1 results in about a 70% chance of a MU=1, a 9% chance of MU=3, and an expected markup of 1.29. At these probabilities, the cost of investing in more non-carbon in Stage 1 than is necessary to meet the cap is outweighed by the potential value of a markup of 1, which would allow compliance with the −20% cap at lower policy cost than if the markup turned out to be 1.5 or 3. Even when it is certain there will be no cap, a high enough learning rate encourages Stage 1 non-carbon investment. In that case, a learning rate of 30% changes the optimal Stage 1 non-carbon share from 5% to 95%. The cost of investing in non-carbon in Stage 1 that is otherwise unnecessary is outweighed by the potential value of a markup of 1, which in this case would allow electricity to be generated from non-carbon at the same cost as conventional generation, thereby freeing up coal and gas resources for other uses in the economy at lower prices and increasing overall economic consumption and therefore social welfare.

6. CONCLUSIONS

Formally taking uncertainties into account in decision-making helps identify near-term investment strategies that hedge against the risks created by uncertainty. This work utilizes a unique modeling framework that represents decision-making under uncertainty with learning and the ability to revise decisions over time in a CGE model that represents the entire economy and can measure social welfare impacts. In the case of electricity investments under technology cost uncertainty and uncertainty in the future external economic environment (model here as uncertainty in future climate policy), the optimal hedging strategy involves investing in more non-carbon generation in the near-term than is otherwise necessary to meet near-term goals alone. The amount of near-term investment depends on the probabilities of future outcomes and the ability to learn so that near-term investments reduce expected future technology costs. Morris *et al.* (2014) showed that in many cases of policy uncertainty Stage 1 investments in non-carbon generation make economic sense because they lower the expected costs of emissions reductions in Stage 2 and take into account potential constraints on the non-carbon technology growth rate between periods. *A priori*, one might expect uncertainty in the non-carbon technology cost to affect Stage 1 non-carbon decisions for the same two reasons, but that turned out *not* to be the case. At least for the cost and policy scenarios explored, cost uncertainty alone does not have a strong effect on Stage 1 strategy.

However, including stochastic technological learning in which the share of non-carbon investment in the near-term affects the probabilities of future technology costs introduces a third motivation for near-term non-carbon investment: the ability to lower the expected cost of the non-carbon technology in the future. Through learning and scale effects, the cost of technologies may decline with increased cumulative capacity. Depending on the rate of technological learning, as well as the expectations about future demand for the technology (driven by the future economic environment, such as future climate policy), the value of reducing expected future costs can provide strong motivation for additional non-carbon investment in the near-term. Results here suggest that under stochastic technological learning, additional near-term investment relative to when there is no learning can be justified at technological learning rates as low as 10–15%, and at the 20–25% rates commonly found in literature for advanced non-carbon technologies, significant additional near-term investment can be justified. Further, as the probability of high demand for the non-carbon technology increase (e.g. because the probability of a stringent cap increases), the value of near-term investments that reduce the expected future non-carbon cost also increases. Investors should account for this value when making investment decisions.

From a modeling perspective, the inclusion of stochastic technological learning is a valuable step beyond the traditional learning-by-doing curves. While LBD curves capture the fact that changes in technology cost come at the expense of investments in the technology, they fail to capture the uncertainty surrounding how much investments will reduce future costs. The formulation presented here captures both of these effects, capturing the uncertain impact of investments on future costs by having investments affect the probability distribution of future costs. We find it can be socially optimal to invest more in non-carbon technology when the rate of learning is uncertain compared to the case where the learning rate is certain. The uncertain nature of technological learning encourages increased investments in order to lower the probability of a high cost outcome and increase the probability of a low cost outcome. Increasing marginal costs produce an asymmetric loss function that under uncertainty leads to more near-term non-carbon investment in attempt to avoid the situation of high non-carbon costs and an external economic environment that creates high demand for non-carbon technology.

These results have policy implications. In the model setup, the benefits of technological learning are fully realized and taken into account by the central planner in identifying the optimal near-term strategy. However, in a more realistic industry structure where there is competition and assuming technological learning benefits spillover to competitors or are not fully captured by the private sector investors, there may be underinvestment in non-carbon technologies compared to what is socially optimal. In this case, there may be need for government policy to encourage private investment in non-carbon technologies. Policies requiring the use of non-carbon technologies, demonstration projects, or tax incentives could be used in the near-term to encourage private investment in non-carbon technologies, and could help lower the expected cost of those technologies in the future.

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