# Energy Technological Change and Capacity Under Uncertainty in Learning

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***Abstract*—This paper explores the role of *learning* in managing the capacities of existing and emerging energy technologies. Specifically, we address how uncertainties in learning rates impact R&D investments into a range of electricity generating technologies. Understanding managerial strategic response under learning uncertainty is particularly important as decision makers face competing R&D portfolios, dwindling and unstable financial resources, and an imminent energy policy. We develop a risk-minimizing optimization model of an abridged global energy system to investigate the effects of uncertainties in technological learning on electricity capacity additions. Addressing the risks associated with uncertainties in technological learning is relevant to distill cost-effective decisions, and to develop risk-hedging strategies. We find that 1) the willingness to hedge against the inherent risks associated with uncertainty in energy technological learning is positively correlated with the risk premium; 2) near-term or early investments are required to achieve a mix of sustainable energy technological portfolios as a hedge against R&D uncertainty; and 3) the management of electricity generation capacities under learning uncertainty allows decision makers to chart a more prudent intermediate path for energy technological growth through the creation of a more diversified technological portfolio.**

***Index Terms*—Energy, investments, learning, research and development, risk, technological change, uncertainty.**

## I. Introduction

To MITIGATE the adverse environmental effects of climate change, anthropogenic greenhouse gas emissions must be reduced. Most often, reductions in the concentrations of greenhouse gases are achieved either by reducing their sources or by increasing their sinks [53]. Yet as global energy use increases and consumption patterns intensify, technologies that are currently economic are not sufficient to halt, let alone reverse the ongoing environmental damage that these sources of carbon dioxide emissions cause. This dilemma highlights not only the relevance of research and development (R&D) in producing new technologies, or in retrofitting old technologies with emissions-capturing accessories, but it also projects the significance of technological learning-by-doing[1] in making emissions abatement[2] and renewable energy technologies economically competitive. At the same time, the energy technology landscape is under the influence of different and multiple uncertainties including demand fluctuations, uncertainties in the type and stringency of environmental policies, and unreliable R&D financial wherewithal. Furthermore, one of the greatest uncertainties in this process, and thus one of the most economically sensitive, is the learning curve associated with technological innovation. Uncertainty in learning is central to investment decisions that are irreversible, long-lived, and are highly impactful on energy firms' profitabilities. With costs and, essentially, profits at stake, this is a major problem confronting the management of investments that energy firms make.

Following the work by Wright [38] and Hirsch [47] that demonstrate how costs fall with cumulative output in the production of airframes and machine tools, more studies show the existence of learning curves across different industries [51], [52]. The scope of learning also involves knowledge acquisition at the organizational level, see [40] for a review. In this paper, we propose that the process of learning can be realistically evaluated, and thus put into economic models of emerging technologies, providing a way to help decision makers make cost-effective choices among competing emissions abatement and/or renewable energy R&D technological portfolios. Perhaps the most important first step to such a conceptualization is to demonstrate that while the economics literature largely assumes technological change to be an exogenous parameter, and thus unpredictable, it is actually an endogenous one, and hence predictable. For example, top-down models predominantly use an abstract abatement cost function without thoroughly examining how this function is impacted by technical change [10], [12], [19]. Models such as these use a production function [9] or cost function approach [10] to initiate output reduction or input substitution or both, but ignore the historical evolution of technological change, particularly as it relates to increases in efficiency through learning. Sectoral optimization models use a similar approach that also represents technological change exogenously as an emerging trend of aggregate growth, not as an endogenous function of investment. In contrast, we argue that the endogeneity of technological change is evident in the recurring cycle between the impact of investment or capital on technology, and the impact of technological growth on capital through increases in productivity that emanate from cost reductions. Further, we propose that factoring in these uncertainties endogenously increases the accuracy of cost-constrained risk-minimizing models, improving decision makers' ability to

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[1] *Learning-by-doing* and *learning* are synonymous and are used interchangeably in this paper.

[2] We define emissions abatement as the reduction of carbon emissions below the business as usual levels.

plot the future trajectories of developing emissions abatement technologies.

We draw on [15] and [20], who observe that future characteristics of technologies are not known *ex ante*, but are the outcomes of the uncertain results of climate change policies and of R&D and investments. Weyant and Olavson [37] classify uncertainty in technological learning as the most important element of modeling endogenous innovation precisely, because the nature and the impact of a developing or emerging technology are difficult to predict. They suggest the modeling of two aspects of uncertainty in induced technological change: major innovations achieved through the process of learning-by-doing, and heterogeneity and discontinuity. Some prior studies consider these factors, but they have limitations. For example, some researchers have addressed uncertainty through sensitivity studies, which are unsuitable for risk-hedging outcomes in a *bottom-up* context [32]. Other studies, such as [30], have applied scenario analysis, which are based on the premise that the model structure is perfect, and do not detect or measure errors due to specifications. In this paper, we address both learning-by-doing and heterogeneity from an engineering systems optimization viewpoint, which allows us to develop an encompassing portfolio of energy technologies under an intertemporal optimization model with specifics pertaining to an aggregated technology representation. We acknowledge that greenhouse gas emissions derive from many sources, but the energy sector—especially electricity generation—is the principal culprit, and thus forms the focus of this analysis.

In addition to the uncertainties inherent in predicting future investments and policies, the various domains of learning present a challenge for modeling its effects. Grübler [14] identifies a number of learning contexts, and the types of learning that derive from them. For example, production processes rely on learning by doing; in the use of materials or technology, learning occurs by using; R&D efforts that require social interaction encourage learning-by-interacting. Research work has developed more detailed parameters for several of these learning domains. Argote and Epple [1] define learning-by-doing processes in manufacturing as increases in productivity as organizations gain experience in production; Criqui *et al.* [8] define learning-by-using as the user's increase in use efficiency of a product or process. In the context of energy framework, we ascribe to the parameterization of endogenous learning as a function of cumulative experience, measured by cumulative installed capacity [13], in a process that is uncertain. Under this representation, costs and uncertainty are assumed to decrease with increasing scale of application. This definition assumes no distinction between learning or experience and economies of scale.[3]

This paper makes three contributions. First, we provide a more consistent representation of how electricity technologies penetrate the energy system. We propose that learning curves, with their uncertain effects on induced technical change, are a necessary addition to energy systems modeling. Second, we provide a template to inform stakeholders in the energy sector of how best to determine the optimal trajectory of investments given uncertainty in technological learning. Notably, investments must be distributed across technology clusters. This is consistent with investment behavior under uncertainty [44]. While the strength of this contribution is modulated by its conformance to established results [20], we see it as a contribution in this domain because the irreversibility, nontransferability, and long-term commitments of investments in these physical assets is a distinguishing factor when focus is strictly on uncertainties in learning. Third, we provide policy makers with a clearer path toward robust climate change technology policy that suggests the need for policies that will drive *early* investments rather than discourage or delay investments in contrast with Dixit and Pindyck's notion [6], see pages [48]–[50]. These three contributions—impactful modeling, informing stakeholders of distributed investments, and informing policy makers of near term investments—will shape the global efforts into R&D and technological learning in both end-use (demand) and production (supply) technologies. We acknowledge that cost effectiveness is one of the most crucial elements in campaigns to reduce carbon dioxide emissions, and we hope this model will facilitate efforts to develop cleaner, more efficient energy technologies. The International Institute for Applied Systems Analysis (IIASA), where this research was initiated, provides the environment to achieve these objectives and make these contributions.[4]

The rest of this paper is organized as follows. Section II reviews the literature on technological learning and uncertainty. Section III defines the core elements of the deterministic model, and it lays out our proposed modifications for stochastic optimization. This section also defines the model parameters and the characteristics of the technology scenarios and clusters. Section IV explains the scope and framework of energy conversion processes and the associated demand-pull, technology-push structure of the single region aggregated model. Section V discusses the outcomes of the optimization routines and offers insights into implications for firm strategic decisions and a guide for energy technology policy. Section VI concludes, and suggests frontiers for future analysis.

## II. Background

Possibly the most severe scientific debate with far-reaching policy implications concerns the role of energy technological change in climate change mitigation [16]. The driving forces—both external and internal—of technological change are familiar topics of research among engineers, technologists, and economists, and managers. Over the last two decades, these issues have increasingly dominated the discussion on global climate change. Indeed, policies that steer technological learning and change on a global level rely on the outcomes of these

[3]Economies of scale refer to the decreases in the average cost of production that come with an increase in production levels, assuming a constant level of technology. Economies of scale are not a source of technological advance, but rather a characteristic of production. However, the two concepts are often intertwined, as increased production levels can bring down costs both through learning-by-doing and economies of scale (see Chapter 2 of IPCC WG 2 of the 4th Assessment Report).

[4]IIASA is an international research organization that conducts policy-oriented research into problems like climate change that have a global reach and can be resolved only by international cooperative action, or problems of common concern to many countries that need to be addressed at the national level, such as energy security, population aging, and sustainable development.

debates. In this section, we draw on two research streams to review the building blocks of these larger issues: the evolution of endogenous technological learning and the uncertainty surrounding it and its outcomes.

### A. Endogenous Technological Learning

Formally, learning emerged in economics with the concept of the learning curve. In his seminal paper, Wright [38] observes that the time required to assemble an aircraft decreased with increasing production levels. On a log scale, this observation plots as a straight line, and is captured in the predictive equation,

$$y = ax^{-b} \tag{1}$$

where $a$ is the time (hours) to manufacture the first unit, and $x$ depicts the cumulative number of units produced; $y$ is the time to produce the unit number $x$, and $-b$ is the slope for the improvement in time in producing the units—this slope represents the learning rate or the elasticity of learning.[5] Mishina [25] highlights this relationship, explaining that various terms associated with it—experience curve, learning curve, progress function—all refer to the same phenomenon but emphasize a slightly different aspect of it: the process, the cause, and the outcome of the cost behavior, respectively. Most important for our analysis is that the mathematical relationship underscored by this linearity in the log-scale suggests the applicability of learning curves for predictive purposes. Empirically, the learning curve has been studied across different industries: pricing model in the chemical processing industry [50]; spillover effects of learning in the semiconductor industry [48]; productivity improvement in the manufacturing industry [39]; improvement in a service industry [43].

One of the earliest approaches to endogenizing technological change, by Nordhaus and van der Heyden [31], establishes the process of learning-by-doing in the form of cost reductions as a function of the cumulative output of a technology. We build on this basic learning curve framework to analyze the evolution of future energy technology portfolios under uncertainty in learning. We draw on Clarke and Weyant [7], who posit that technological change that merely responds to the passage of time is exogenous, but that the notion of induced technological change encompasses the underlying but realistic assumption that research and innovative decisions by firms and individuals are considerably influenced by private costs and reward for innovation. In other words, induced technological change is endogenous to the social and economic system because investments are needed to foster induced technological change. Nordhaus [29] highlights this concept by introducing a compact representation of induced innovation into the dynamic integrated model of climate and the economy (DICE); he finds surprisingly modest implications for long-term climate policy. Messner [22] also incorporates learning curves for six electricity technologies in a simplified version of the (deterministic) energy systems-engineering model (MESSAGE). This approach has led to a number of important insights for further modeling of endogenous technological change [26], [27].

However, as complexity and computational demands increase, the difficulty of precisely tracing a learning curve produces a number of drawbacks to this type of modeling. Energy technological change is riddled with uncertainties, among them are the difficulties in predicting the outcomes of individual R&D efforts and the lack of knowledge about what the future holds or the possibilities of radical breakthroughs. For example, because Messner [22] modeled learning rates as deterministic, the model could not accurately capture uncertainties in the learning trajectory. Incomplete knowledge about the dynamic competition between energy technologies—such as wind, solar, geothermal, and established conventional options—along with the likely discontinuity of one technology when dominated by another, further broaden the uncertainty arena. The influence of uncertainty on the profit margin is a key component of firm-level investment decisions into these energy technologies.

One of the primary disadvantages to modeling learning-induced technological change arises from the difficulty in identifying the mechanisms behind it. For example, [11] highlight energy R&D as a likely force driving learning curves.[6] They underscore the difficulty in understanding how learning influences change. For example, there is an aspect of learning that is induced by policy where reduced learning results in lower output or development of some fossil-energy intensive technologies. Others [36] cite, among other factors, additional drawbacks of tracing the effects of learning-by-doing in endogenous technological change. Particularly troubling is the deficiency in empirical data on the learning rates in some new energy technologies, which hampers an adequate representation of the learning paradigm in models. Clarke and Weyant [7] argue that the inclusion of learning curves in these models can induce path dependences, and in turn lead to *lock-in* of a given technological pathway. These issues underline the relevance of factoring in uncertainty in energy technological learning as considered in this paper.

### B. Uncertainty in Learning

The importance of modeling uncertainty in learning comes from its criticism in literature. Dutton and Thomas [45], in a survey of more than a hundred studies on learning curves, show significant variations in learning rates. These differences underscore the limitation of taking learning as deterministic. Nonetheless, adopting the learning curve has several merits. First, the availability of historical time series on costs and outputs (or performance) provide a framework for predictive purposes, and thus, for effective planning. Second, the empirical literature provides outcomes that show how firms learn from past experience, and the results are consistent with models of the learning curve. Third, using a single parameter to capture a complex process empowers easy computation and analysis of computable general equilibrium models.

[5] From (1), by definition, the elasticity of learning, $\varepsilon$, is

$$\varepsilon = \frac{dy}{dx}\frac{x}{y} = -\frac{ab}{x^{b+1}}\frac{x}{ax^{-b}} = -\frac{ab}{x^{b+1}}\frac{x^{b+1}}{a} = -b.$$

[6] A discussion of the aspects of R&D and "learning by doing," the main contributors to technological change that are complementary yet interlinked can be found in [34].

Uncertainty in technological improvements manifests in different ways. For example, the costs of energy technologies are subject to future carbon policies as policy makers grapple with how to address concerns on climate change. The uncertainties surrounding the timing and magnitude of these policies [4], [35], [54] influence the cost projections on these technologies. Another dimension of uncertainty in learning is the outcome of R&D investments. The success of an R&D program is conditioned on a range of probable parameters, such as the consistency of research funding, the feasibility of demonstration projects such as carbon capture, and storage without social issues such as NIMBY,[7] the level of maturity of the technologies, and the state of diffusion/adoption of the base technologies.

The relevance of uncertainty in energy technological change fuels the concept of modeling it as an endogenous process, in both R&D and technological learning models. On the R&D front, Baker and Adu-Bonnah [2] combine uncertainty in energy-related technological change with uncertainty in environmental damages to analyze socially optimal investments in technology research and development. They consider "riskiness" of R&D projects by comparing projects that have a deterministic return against projects with the same expected value but outcomes of either failure or breakthrough. They show that the socially optimal investment in technologies that pivot down the cost curve, and therefore reduce the marginal abatement cost, is higher for riskier projects than less-risky projects. By extension, they show that the optimal investment in more-risky technologies increases. Along these lines, Baker *et al*. [3] find that optimal investments may increase or decrease in uncertainty depending on the specification of the technologies. And, in a bottom-up approach, Bosetti and Tavoni [41] incorporate a carbon-free backstop technology into the model with the assumption that its cost can be lowered through investments in innovation in the form of R&D. Their innovation outcome is modeled as uncertain.

The central theme of this paper is a general equilibrium approach to address uncertainties in learning rates for electricity generating technologies. On a conceptual level, the progress ratio, the proxy for learning, is highly uncertain because its future value is difficult, if not impossible, to predict. Certainly, historical estimates give valuable information on the trend of learning, but new developments are likely to alter that trend. Thus, an extrapolation of initial trends can lead to one of two outcomes on the progress ratio: an overestimation, which will alter profit margins; or an underestimation, implying risks in technology investments that have the potential to be more expensive than initially expected. Either of these two outcomes may potentially drive a firm out of business because overestimation dampens profitability; and underestimation leads to competitive weakness that also negatively impacts profitability.

## III. Model

In this section, with the aid of relevant and descriptive optimization models, we present our basic methodological approach to endogenizing technological learning. The technical details involved in this approach highlight a number of programming complexities. For example, the formulation of the learning curve is nonlinear because it involves an increasing returns property that yields it as a nonconvex optimization problem. Thus, arriving at a global optimal solution is difficult because of several local optima in these nonlinear problems. Following the example in [5], and with the aid of a segmentation procedure, we transform the problem into mixed integer programming (MIP) by linearizing the nonconvexity of the original problem through a series of piecewise approximations of the cost curve explained in the Appendix. The model structure is specific to the energy system with emphasis on the electricity sector, which we discuss further in Section IV.

### A. Deterministic Model

We adopt the traditional form of expressing the experience curve represented in (1) to define the relationship between investment cost and the cumulative installed capacity; that is

$$C_{\kappa,t}(K_{\kappa,t}) = a \cdot K_{\kappa,t}^{-b_\kappa} \tag{2}$$

where $C_{\kappa,t}(K_{\kappa,t})$ is the specific cost per kW for electricity output in a given technology, $\kappa$, at time, $t$; $K_{\kappa,t}$ is the corresponding cumulative capacity, $b_\kappa$ is the learning elasticity by each technology, and $a$ is the unit specific cost. The elasticity of learning measures how the change in cumulative capacity influences the specific cost. Thus, a *doubling* of capacity will reduce specific costs by a factor of $2^{-b}$, which is the progress ratio[8] $\mathrm{PR}_\kappa$, for a given technology

$$\mathrm{PR}_\kappa = 2^{-b_\kappa}, \quad b_\kappa = -\frac{\ln \mathrm{PR}_\kappa}{\ln 2} \tag{3}$$

This form is consistent with earlier representations in [5] and [20]. The progression of cost reduction is influenced by two important parameters. First, the cost reduction is sensitive to the value specified for the progress ratio. We tackle this sensitivity through probability distributions on the mean historical estimate for a given technology. Second, the initial cumulative capacity and corresponding cost are crucial in determining the expected progression of learning in the technology. For our simulations, we maintain the same initial capacity for each realization in the several scenarios from the distribution. The objective function is maintained by considering the total cost as an accumulation of the specific cost in (2) given by

$$\mathrm{TC}_{\kappa,t}(K_{\kappa,t}) = \int_0^{K_{\kappa,t}} a \cdot K_{\kappa,t}^{-b_\kappa} \cdot dK \tag{4}$$

$$= \frac{a}{1-b_\kappa} K_{\kappa,t}^{1-b_\kappa}. \tag{5}$$

This total cost function is quite realistic, because it represents the accumulation of the instantaneous specific costs over time. As this is a learning model, the specific cost (or instantaneous cost) is a power curve based on the cumulative capacity (or knowledge stock) for each technology. The question on the possibility of other cost structures is valid; however, to the best of our knowledge, other models that have deviated from this

[7] Not In My Back Yard.

[8] The progress ratio relates with the learning rate, $LR$ as, $LR = 1 - PR$.

form end up taking learning as exogenous. The investment cost $I_{\kappa,t}$ in a technology $\kappa$ at time $t$, is captured by the marginal cost of the intertemporal total cost values derived from the piecewise segmentation of the total cost curve

$$I_{\kappa,t}(K_{\kappa,t}) = \mathrm{TC}_{\kappa,t} - \mathrm{TC}_{\kappa,t-1}. \tag{6}$$

This process of segmenting or *piecewise* linearizing the cumulative cost curve requires the introduction of an exogenous parameter—the number of segments, $s$. The discretization of the total cost into linear segments constitutes a problem in defining the consecutive points of interpolation or kinks based on $s$. With $s$ known *a priori* and exogenously, and within the estimated boundaries of the curve, the segments for $i = 0, \ldots, s$ are found using[9]

$$\mathrm{TC}_{i,\kappa,t} = \mathrm{TC}_{0,\kappa,t} + 2^{i-s}\left(\mathrm{TC}_{\max,\kappa,t} - \mathrm{TC}_{0,\kappa,t}\right)\sum_{i=0}^{s-1} 2^{i-s} \tag{7}$$

where $\mathrm{TC}_{0,\kappa,t}$ and $\mathrm{TC}_{\max,\kappa,t} = \frac{a}{1-b_\kappa}(K_{\max,\kappa,t}^{1-b_\kappa})$ represent the initial and maximum total costs respectively, with the capacity limits $K_{0,\kappa,t}$ and $K_{\max,\kappa,t}$ given as inputs to the model. For a review of the details of the logical constraints for segment activation, and additional interpolation constraints, see the Appendix and [5].

The decision maker or planner wishes to determine the optimal capacity levels at time $t$ by technology $\kappa$, $K_{\kappa,t}$ that minimizes the total system costs $F^T$, which comprise the costs of technologies and conversion processes not included in learning, $F$, and the learning costs over time as

$$\min F^T = F + \sum_\kappa \sum_t I_{\kappa,t}(K_{\kappa,t})\delta(t) \tag{8}$$

where $\delta(t)$ is the discount factor. Without learning, the objective function reduces to minimize the total system costs, such that $F, F^T = F$. Specifically, there are no learning costs. These are strictly the costs of the conversion processes, $F$, are the costs incurred in other transformations described in the reference energy system in Section IV. For example, one technology extracts coal from nature, another technology converts coal to liquid; a different technology, coal power plant, converts coal to electricity. Simplified Fig. 5 shows the transformations for different resources with the electricity generated providing other services including heating, transportation, and even used in initial resource extraction and transformations. While these conversion processes are included in the abridged model, the focus of the deterministic model is on the costs due to learning through changing capacity levels in the conversion to electricity of the primary resources, captured by $\sum_\kappa \sum_t I_{\kappa,t}(K_{\kappa,t})$, and discounted by $\delta(t)$. With technological learning, (2)–(8) define the additional system costs due to learning solely in the electricity generation segments. Note that (8), which contains the learning parameters of the technologies, is a nonlinear, nonconvex function. The objective function, in the absence or presence of learning, is constrained by demands, resource availability, and whether the output of one technology serves as inputs to another.

The deterministic model is similar to the Messner model [22] due to the constraints of the model, and in the way we have endogenized technological learning. The constraints, based on those from the base MESSAGE model [24], are capacity requirements, average utilization, resource extraction, and constraints on the growth of extracted quantities. The standard practice to endogenize learning is to make the specific cost a function of the cumulative capacity. Nonetheless, we differ in the mechanism used to capture learning. Specifically, in the Messner model, cumulative knowledge acquired in the learning process is captured strictly as the discounted product of investment and cost of investment. The cost of investment is a function of cumulative investments. In this model, we use the *power curve* cost model in (2), which is then aggregated over capacities, see (4). Our investment costs are, thus, the intertemporal total cost values derived from the segmentation of the cumulative total cost, (6). This approach has the advantage of capturing time-specific investment effects on capacities compared with Messner's aggregated total costs.

## B. Stochastic Model

Time series observations of energy technology costs and capacity expansions show that technological learning is stochastic. For example, [21] and [49] show that technological learning rates commonly follow log-normal distributions for energy conversion and electricity generating processes. The underlying factors driving uncertainty in learning include fluctuating demand, changing costs of energy resources, unknown future carbon policies, uncertain outcome of R&D activities, inconsistent research funding, the feasibility of demonstration projects, and the state of maturity in the technology $S$-curve. To mitigate the financial risk of planning based on deterministic learning, we factor uncertainty in learning into the deterministic model, and introduce uncertainty into the learning elasticity. The parametric representation of the technologies in an energy system optimization framework subjects the learning parameter to a range of values that capture the uncertainty spread. We consider the minimization of risk under constrained cost. In this stochastic model, the progress ratio, PR, is uncertain; we take this progress ratio from probability distributions as input. The assumptions surrounding the spread on the mean progress ratio are explained in Section III-C. Fig. 1 illustrates the model dynamics.

The mean and variance of the progress ratios are estimated for each technology from their historical cost and output performance, and the statistics are subject to the log-normal distribution to generate multiple scenarios. We use a risk measure [23],[10] upper mean absolute deviation, as the framework for risk assessment. This measure is the minimization of the discounted expected underestimation[11] of total system costs attached

[9]This segmentation procedure leads to unequal length segments and a shorter, but steeper curve occurs in the first segment. Our results show no appreciable changes for segments greater than 10, but routines take longer run-time.

[10]The stochastic model presented is not endogenous, because the technology costs are exogenously and randomly sampled without recourse to how the investment cost is affected by increasing capacities.

[11]In competitive electricity markets, cost underestimation attracts very stiff consequences because a firm may be forced to quit the market.

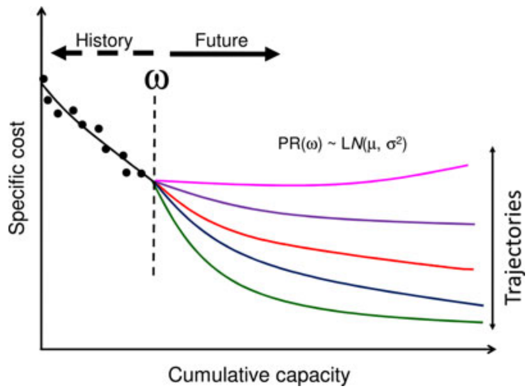


Fig. 1. Illustration of the dynamics in the model.

to the economic risk of a given technology strategy. The stochastic learning elasticity, $b(\omega)$, is derived from (3). For each realization of $\omega$, a new construct yields $I_{\kappa,t}(\omega)$, following (2)–(6). $\omega$ is an element from a probability space that indicates the dependence of the learning elasticity $b(\omega)$ on a random event characterized by a probability measure. Thus, the vector of investment cost, $I_{\kappa,t}(\omega)$ is stochastic. This implies that the aspect of the system cost due to learning, $\sum_\kappa \sum_t I_{\kappa,t}(K_{\kappa,t})$, for a given vector of $K_{\kappa,t}$, follows from the probability distributions on $b(\omega)$. Thus, an underestimation of the expected cost incurred is the positive difference between the deterministic cost and the cost for each realization of $\omega$

$$\sum_t \max\{0, [I_{\kappa,t}(\omega)(\mathbf{K}) - I_{\kappa,t}(\mathbf{K})]\}. \tag{9}$$

Taking expectation over the realizations of $\omega$ on the deterministic cost function yields technology capacity strategies that reflect their economic risks

$$\min \bar{R}(\mathbf{K}) = E_\omega\left(\sum_t \max\{0, [I_{\kappa,t}(\omega)(\mathbf{K}) - I_{\kappa,t}(\mathbf{K})]\} \cdot \delta(t)\right). \tag{10}$$

Subject to the cost constraint such that

$$F^T(\mathbf{K}) \leq (1+f)\,F^T(\mathbf{K}^*) \tag{11}$$

where $\mathbf{K}$ is a vector of capacities by technology and by time, $K_{\kappa,t}$, $F^T(\mathbf{K}^*)$ is the optimal objective function value of the total system costs with deterministic learning in (8). On the right-hand side of (11), is $f \cdot F^T(\mathbf{K}^*)$, the premium the decision maker or planner will pay to reduce the risk associated with uncertainty in the learning elasticity, where $f$ is a fraction of the optimal total cost in the deterministic setting, and it is exogenous to the model—the decision maker, based on risk tolerance determines its value. We note here that as $f$ increases, the total system cost increases, and the risk reduces.

*Proof:* Consider the problem

$$\begin{aligned}&\min \bar{R}(\mathbf{K})\\ &\text{subject to } -F^T(\mathbf{K}) \geq -(1+f)F^T(\mathbf{K}^*)\end{aligned} \tag{12}$$

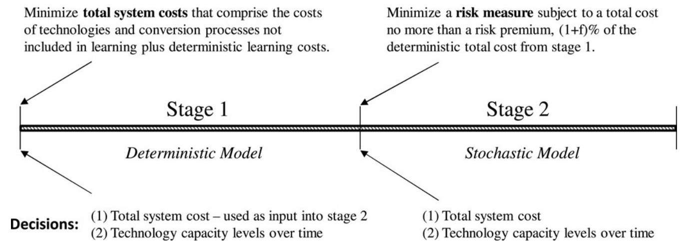


Fig. 2. Sequence of the two-stage optimization procedure.

The Kuhn–Tucker conditions on the Lagrangian

$$\mathcal{L} = \bar{R}(\mathbf{K}) + \lambda(F^T(\mathbf{K}) - (1+f)F^T(\mathbf{K}^*)) \tag{13}$$

i.e., the first order conditions on the multiplier $\lambda$ and $\mathbf{K}$ yield the simultaneous pair

$$F^T\mathbf{K} = (1+f)\,F^T(\mathbf{K}^*) \tag{14}$$

$$R'(\mathbf{K}) = -\lambda F^{T'}(\mathbf{K}). \tag{15}$$

The solution to (14) and (15) implies that as $f$ increases, the risk measure decreases. This is because the cost function, $F^T(\mathbf{K})$ is convex, making $F^{T'}(\mathbf{K}) \geq 0$. Thus, any increase in $f$ in (14), increases $F^T(\mathbf{K})$, which in turn makes the marginal change in risk, $R'(\mathbf{K})$ in (15) decrease.

In addition to observing the correlation between risk hedging and risk premium, our goal is to demonstrate how this commitment is distributed across energy technology categories. Including this risk premium as a constraint on the total system cost under the stochastic model transforms the problem into a two-stage process; see Fig. 2—the first stage arrives at the deterministic learning solution, $F^T(\mathbf{K}^*)$; we use this objective function value of the deterministic learning outcome in (11) as a constraint on the second-stage stochastic model such that the capacity choices that minimize the risk measure produce a total cost no more than $(1+f)\%$ of the deterministic cost. Thus, the model chooses $\mathbf{K}$, by technology and over time, that minimizes the risk measure in the stochastic model.

## C. Model Parameters

Here, we describe the properties underlying the parameters of the model. The rapid decline of investment cost with every doubling of cumulative installed capacity is typical for some technologies with high learning elasticities, but specific shapes depend on each technology. For example, accelerating the development of technologies for generating photovoltaic (PV) electricity implies making the technologies cost competitive. Thus, for PV cells, gas turbines and windmills, the cost per unit of output has declined steadily as volume has increased [46]; see Fig. 3. This explains why progress ratios typically range between 0.65 and 0.95 for all technologies and even narrower for energy technologies [6].

One of the assumptions governing the probability distribution on the progress ratio is nonnegativity[12] of the values from

[12]This does not imply nonnegativity in learning elasticity, see (3). In other words, values greater than 1 will lead to negative learning rates or increasing cost per doubling in capacity.

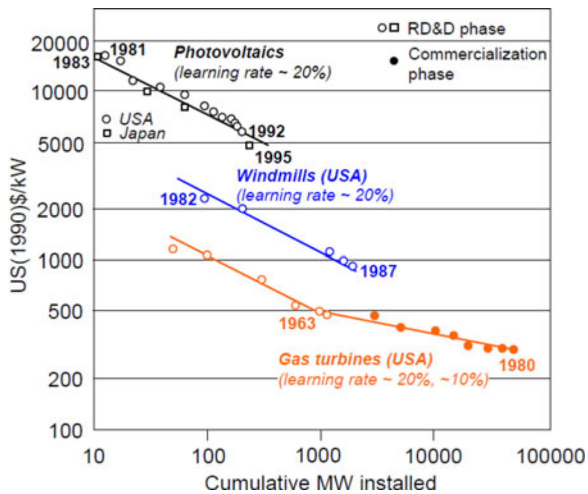


Fig. 3. Technology learning curves for PV, wind, and gas turbines. Sourced from [46].

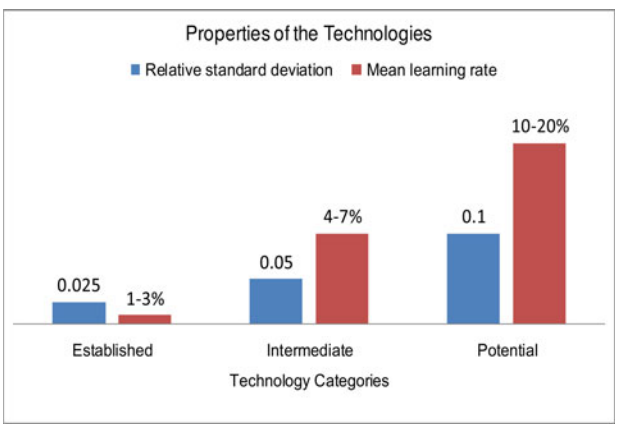


Fig. 4. Learning characteristics: Mean progress ratios and relative standard deviations.

the sampling. In this analysis, we use the normal distribution, which is symmetric. While this distribution is limited by the disadvantage of imposing cutoffs at the tails with less likelihood of the option of technological failure, it is adequate for the range of progress ratios of the technologies under consideration. We put the technologies into three categories—established, intermediate, and potential. The *established* category contains mature technologies with only small changes in their learning trajectories; these are assigned the lowest class of uncertainty. The *intermediate* cluster contains technologies that are readily available and show significant variance over their mean progress ratios. The *potential* class comprises technologies that have not been deployed on a large scale, such as carbon capture and storage, or those that still have social acceptance barriers, such as nuclear technologies. We assign a relatively high spread to this latter category because it holds the potential to revolutionize the energy landscape. In addition, we have assumed that uncertainty in the progress ratio of a category is an increasing function of its mean. Fig. 4 shows the properties of the categories.

The interdependence between some of the technologies, such as the carbon capture and storage technologies for gas, coal,

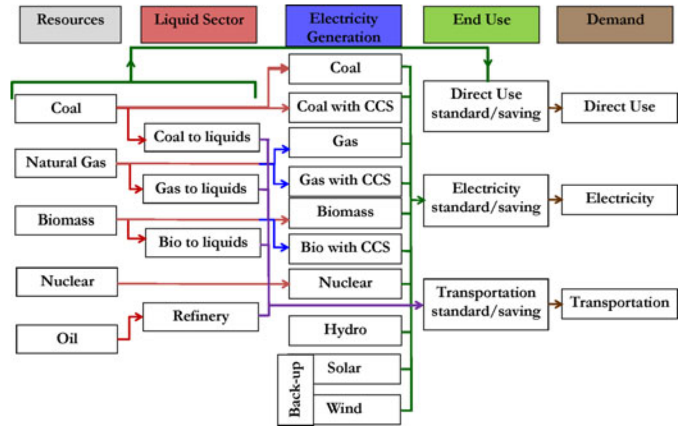


Fig. 5. The full version is the 11-regional MESSAGE energy system [33].

and biomass plants, is addressed by having them perfectly correlated in the data generation routines. This interdependence is important because the development and deployment of these technologies are not entirely independent of one another. Sampling from the joint distribution of learning rates for technologies with interdependent parameters is achieved with the aid of the latin hypercube sampling (LHS) method [18]. The sample size, $N$, for this analysis range from 500 to 1000. The response of the optimization routine degrades in time with increasing sample size. However, for larger sample sizes, we observe very marginal differences in the optimal objective function value, implying arrival at a stable solution.

We model carbon prices to increase over time in accordance with IPCC's scenario database with $CO_2$—equivalent concentration target of 670ppmv. The spread of carbon prices—made for the terminal year, 2100—was extrapolated backward to 2000 using an assumed discount rate of 5%. Carbon prices come into play in the model in the conversion costs of the resources. The uncertainties in the progressions of related technologies (those with carbon capture and storage) are modeled by their joint distributions. We use a risk premium, $f$ of 3%, as system costs show no observable differences above this threshold.

## IV. Simplified Reference Energy System

The reference energy system is the structure in which the energy conversion processes and interactions between market-pull and technological-push forces play out. The system is a dynamic network with flows from one energy form to another. Some of these flows translate into energy technologies such as electricity generation from coal or gas power plants. We use a simplified version of the 11-regional MESSAGE energy system illustrated in Fig. 5 [33].

Energy flows in five different stages. These are: 1) extraction from energy resources; 2) primary energy conversion into secondary energy forms in the liquid sector; 3) electricity conversion; 4) transport and distribution of energy to the point of end use that results in the delivery of final energy; and finally 5) the conversion at the point of end use into useful energy forms that fulfill specified demands. In addition, the different sectors of the economy have various demands for useful energy.

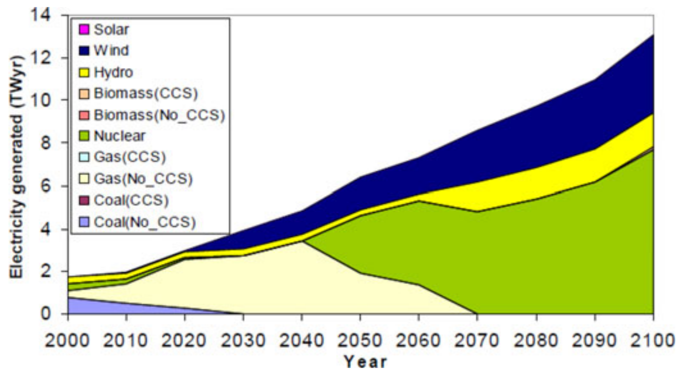


Fig. 6. Intertemporal electricity generation without technological learning.

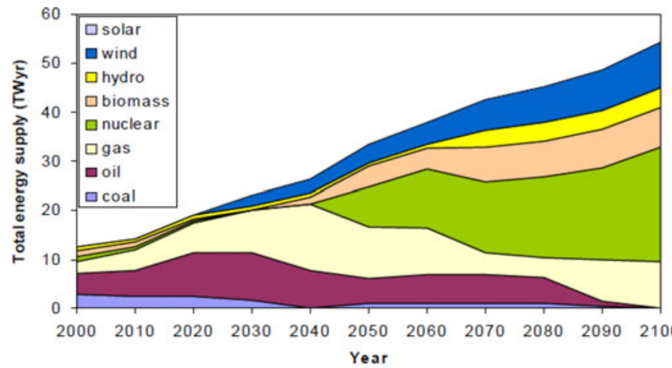


Fig. 7. Intertemporal total primary energy supply without technological learning.

We describe the technologies in terms of their investment, fixed and variable operations and maintenance costs, from which levelized costs are derived, unit size, efficiency, lifetime, and emissions. These characteristics provide the coefficients for the balance constraints and the restrictions on resource availability. The overall objective is to fulfill various demands by utilizing technologies and resources with the minimal total discounted system costs.

We focus on endogenous learning in the electricity sector because electricity generation is the emphasis of this technological learning-by-doing model; however, to aid straightforward implementation and results analysis, we simplify the structure to assume a single world region by aggregating all regional data under the *IPCC SRES B*2 scenario [28] and with demand data assumptions based on [33]. We simplify further by considering only one major electricity technology for each energy carrier. In other words, we do not explore all the existing forms of coal-based technologies for generating electricity, but instead focus on the aggregated data for all technologies in the coal-based cluster. Thus, as shown in Fig. 5, we implement learning on seven electricity technologies—coal, gas, biomass, nuclear, hydro, solar, and wind (with backup)—with an additional three of these seven having capabilities for carbon capture and storage (CCS)—coal, gas, and biomass.

## V. Results and Discussion

We present the results to highlight the differences in model outcomes. First, we show the model outputs in the absence of technological learning. Second, we compare the technology landscape produced from the deterministic and stochastic learning models. In this comparison, we consider both the electricity generated and the total primary energy supply for the aggregated technologies – Figs. 6–9. The electricity generated are the capacities by technology over time. The total primary energy supply curves represent both electric energy and nonelectric energy from other conversion processes obtained from solar, wind, hydro, biomass, nuclear, gas, oil, and coal technologies. Third, we compare the emissions predicted by each model based on the sectors in the reference energy system and on the system aggregate. Fourth, we compare the cost structure of the three models.

### A. No Learning

Fig. 6 shows the energy profile from the technologies when the system cost is minimized without technological learning. The model outputs show that the future of electric power technology will derive from three major sources—wind, hydro, and nuclear. The future dominance, predicted by the model, of these low-carbon technologies over the current options, such as coal power plants, underscores the need for less carbon-intensive technologies if producers are to simultaneously meet growing demand and maintain the stabilization target. On the one hand, this result is more about technology switching due to the growth of carbon prices. In other words, in the absence of learning investments in technologies, future projections of carbon prices will drive the landscape toward a less diversified technological mix. On the other hand, the total primary energy supply in Fig. 7 shows that the carbon-intensive technologies still make relatively significant contributions to the energy technology mix. We infer that this behavior is partly due to the price on carbon through emissions in the generation of electricity while nonelectric conversions suffer less of the carbon *penalties*. Another pertinent observation is that in the absence of endogenous learning, the growth rate of the technologies is significantly high, especially for nuclear, once the carbon price differential makes the technologies cost competitive.

Thus, *moderated* or smooth penetration is not an outcome in the absence of learning. For example, the scale of electricity from nuclear is expected to rise by almost 2 TWyr in the decade between 2040 and 2050. This clearly exhibits implementation hurdles because the scale of capacity increases proffered by the model outcome is not realistic.

### B. Endogenous Learning

Fig. 8 shows the total primary energy supply graph when there is deterministic learning on the left-hand side, and stochastic learning on the right-hand side. First, technologies in the total energy supply graph achieve a higher percentage of up-scaling than without technological. Second, stochastic learning reinforces and modifies this up-scaling by making the technologies penetrate the technology mix in a smoother manner and earlier. For example, in the stochastic figure, the up-scaling of biomass, nuclear, and hydro occurs at least one period—10 years—earlier

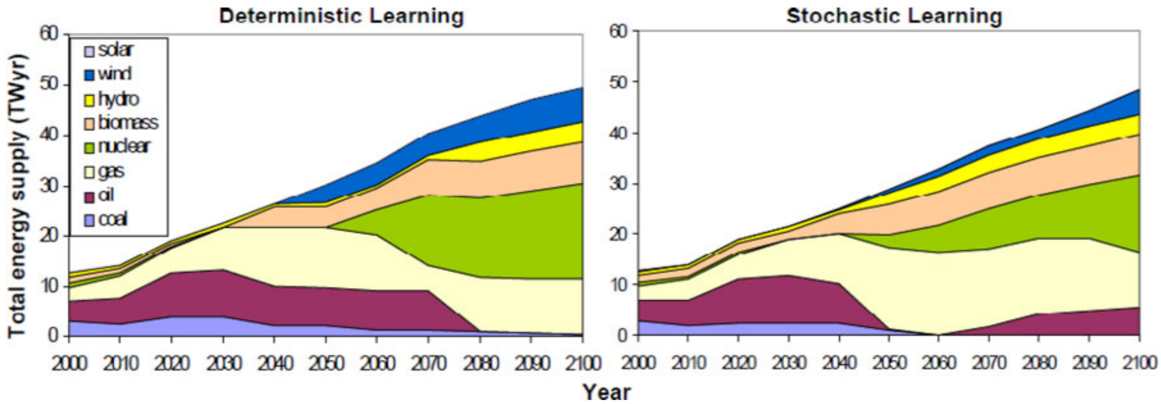


Fig. 8. Intertemporal total primary energy supply under deterministic and stochastic learning.

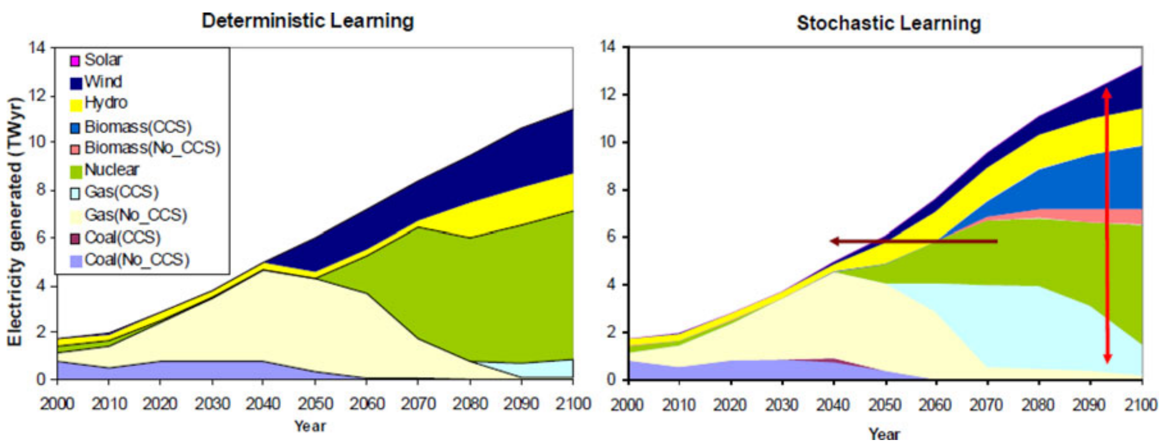


Fig. 9. Intertemporal electricity generation under deterministic and stochastic learning.

than in the deterministic figure, which also shows some technologies penetrating earlier than under no learning, as Fig. 6 shows. This outcome is a result of additional risk-hedging investments; that is, in (11), $f = 3\%$.

With focus on the generation of electricity, these effects are even more pronounced. Fig. 9 shows the generation capacity of electricity required to satisfy targets and demands over the next century, from 2000 to 2100. On the left-hand side is the result of the deterministic model where learning in the technologies is strictly on their mean rates for the capacity of electricity generation. On the right-hand side is the result of the analysis for uncertainty in learning in the technologies. In both figures, year 2010 values show that coal and gas dominate the energy portfolio in meeting demands.[13] Over the following three decades after 2010, both models show no appreciable change in the landscape except for the evidence of carbon capturing in coal technology under stochastic learning. However, by the middle of the century, the substantial penetration of nuclear technology and the carbon capturing options for gas and bio-fuel generate remarkable changes. On the qualitative front, stochastic learning ensures a diversified landscape in the future of electricity generation.

These findings produce two additional conclusions that are instructive for decision making. The first is that meeting and

[13]This is consistent with the World Energy Outlook report of the IEA [17].

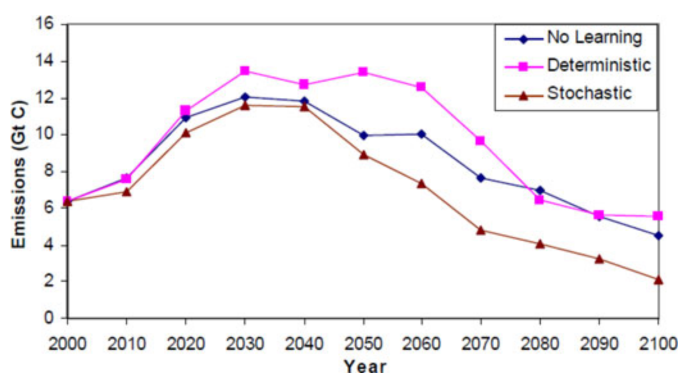


Fig. 10. Total $CO_2$ emissions by model.

maintaining the stabilization target under increasing demand for electric power requires near term investments—as indicated by the brown arrow—into technologies under uncertainty in technical breakthrough and deployment. The second guide to policy and decision making is that these near term investments must be distributed across technology clusters—as indicated by the spread with the red arrow. Moreover, under uncertainty in progress ratio, the penetration of the potential technologies into the energy landscape is smoother than in the deterministic case. This result is intuitive to marginal up-scaling of investments for gradual penetration of the potential technologies rather than

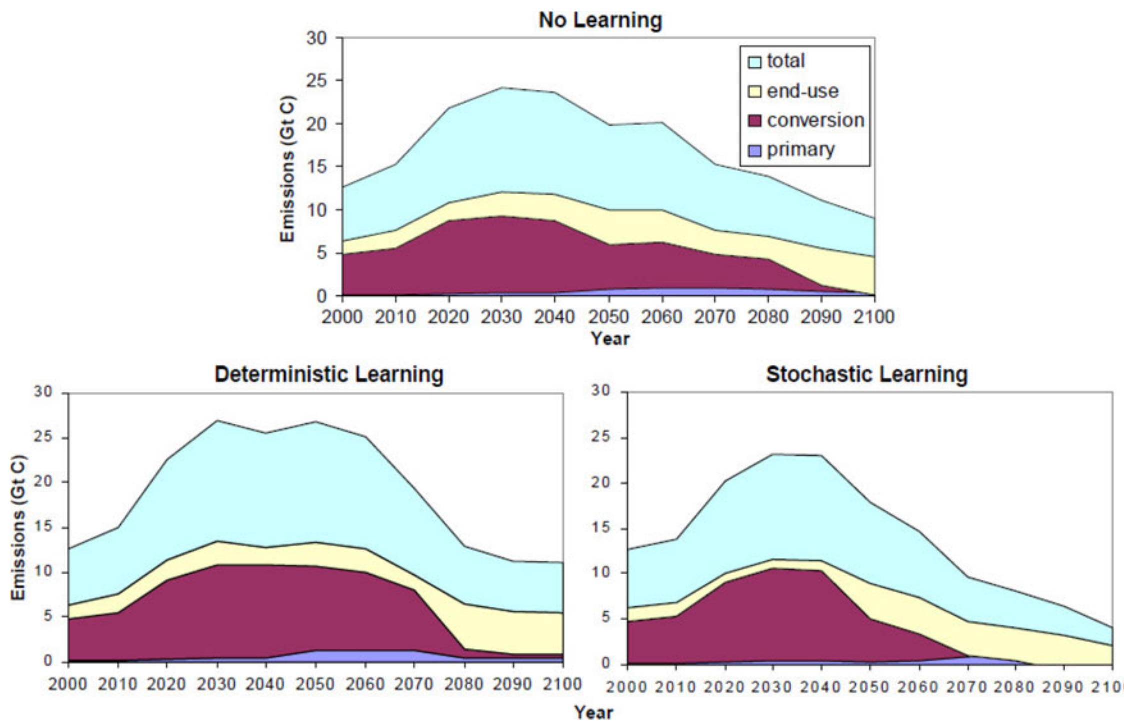


Fig. 11. Emissions profiles.

their abrupt emergence, which is less realistic, as depicted in the deterministic case. These projections are conditioned on the objective of reducing risk as defined by our chosen risk measure.

### C. Emissions

We compare the emissions profiles in the reference energy system under three model structures in Fig. 10. It is not unexpected that total $CO_2$ emissions under deterministic learning are higher than under no-learning scenario because deterministic learning produces a technology horizon that is constrained by the trajectories of the technologies. This constraint can be viewed as the imposition of the assumed mean learning rates on the technologies leaving less variation in the minimization of total system costs.

The no-learning scenario is less constrained, so that minimizing the total system cost in this case gives the model more depth in emissions reduction. The only exception occurs toward the end of the horizon. On the other hand, stochastic learning, which is a super-set of the deterministic scenario, has the lowest total emissions profile. The components of the total emissions indicate that the conversion sector is responsible for over 90% of global emissions (see Fig. 11). It is difficult to ascertain how much of each sector is influenced by technological learning in the electricity industry, but it is evident that the next few decades will witness increasing emissions until the new technologies become dominant. The stochastic scenario sets this dominance earlier, by year 2070, than the no-learning or deterministic scenarios, which predict the new technologies' dominance by year 2080 and 2090, respectively.

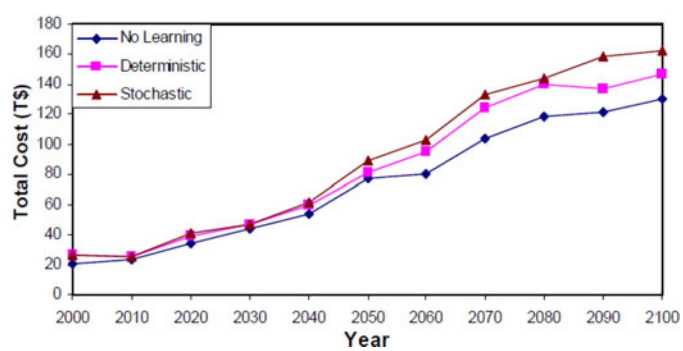


Fig. 12. Total system cost.

### D. System Costs

Fig. 12 derives the total system costs according to each of the three models. Not surprisingly, the stochastic model produces the highest cost over the horizon. The difference between the stochastic cost and those produced from the deterministic and no-learning scenarios depends on the premium that the social planner is willing to pay to hedge against the risk inherent in the uncertainty in technological learning. In the stochastic case, it is the premium against the underestimation of total system costs which we define earlier as the economic risk associated with the output levels in (11).

In addition to the findings on endogenous learning-by-doing (at the end of subsection V-B), we observe that planning to hedge against uncertainty in learning is not an entirely undesirable policy aim. While the absence of technological learning is not optimal, learning with the intent of risk hedging (stochastic learning) has greater advantages in economies of scale than learning that is *locked* in the mean rate from historical observations (deterministic learning). This observation reinforces our recommendation to policymakers that enacting policies to promote incremental investments in energy technologies is crucial to meeting the rise in global energy consumption in a range of environmentally friendly ways.

## VI. Conclusion

We use an intertemporal optimization framework to analyze the effect of uncertainty in technological learning-by-doing on a set of energy technologies. This analysis considers the optimal amount of electricity to be generated over the course of about a century in response to uncertainty in endogenous technological learning and increasing carbon prices. We model technological advances through an endogenous reduction in cost per doubling of cumulative capacity in 10 classes of electricity technologies. We first assume that the progress ratios of these technologies are known with certainty from their historic mean estimates, or expert opinions for emerging technologies such as carbon capture and storage. Second, we then assume these ratios to be uncertain with a log-normal distribution around their mean values. In assigning a range around these mean values, we follow the requirement to make the spread proportional to the rate of learning.

Our results and observations produce three significant findings. 1) Investment into electricity generating technologies is *rightly* riddled with uncertainty in technological learning, and the level of risk the social planner or decision maker is willing to hedge against plays a crucial role in defining the optimal investment policy, and the paths of energy technology evolution. It is logical to postulate that the higher the planner is willing to hedge against the inherent risks associated with uncertainty in learning, the greater the premium to achieve this purpose. 2) The achievement and sustenance of a green economy in the future requires an expanded suite of energy technologies and investments into this expansion should be near term. Technological competition between electricity generation technologies is projected by the penetration of more expensive low-emissions and zero-emission technologies at the expense of established cost-effective technologies, and due to likely changes in the energy or carbon policy. This intuitively suggests that to achieve this green economy, the social planner or policy maker needs to implement more stringent regulatory tools to accelerate early investments and, in turn, early deployment of these alternative technologies. 3) Rather than *resolve* uncertainty in learning by conditioning it on a certain future time, or on the attainment of a given level of generated capacity as we see in earlier models, this analysis considers the investments in this set of electricity technologies as a problem in decision making under uncertainty. We argue that uncertainty is never completely resolved, but with more information, decisions resulting from our intertemporal models inch toward the optimum.

Climate change concerns is making engineering managers and investors in the energy sector consider *end-of-pipe* technologies such as carbon capture and storage, and the adoption of other cleaner renewable resources such as biomass, wind, and solar technologies. In providing prescriptions on electricity technology capacity expansion strategies, this paper is of relevance to the practice of engineering management because to effectively mitigate the incidences of climate change, meet the rising global demands for energy, and hedge against the inherent risks associated with uncertain R&D outcomes, managerial action should be geared at near-term technology investment decisions. By extension, we argue that while near-term risk-hedging costs are high and uncertainty in R&D outcomes are never completely resolved, investment responses to uncertainty in learning do eventually lead to overall emissions reductions and, by extension, cost reductions especially under severe carbon prices. This is particularly true because capacity expansions define a more diversified technology set with technology substitutions to hedge against policy changes. In other words, investment returns are guaranteed.

A general study of technological learning may be informative, but the influence of uncertainty in learning is not *monotonic* across different application environments. The characteristics of application environments differ with respect to service versus product domains,[14] industries with incremental innovations versus those with competence-enhancing improvements.[15] Our proposition is based on three reasons—1) the degree of asset specificity which influences the industry structure in the energy industry is not easily or directly replicated in other applications; 2) investments in the energy environment are usually irreversible, and have long-life spans; and (3) the learning function used in the study is well-suited to the energy domain, because we have used a progress ratio that captures the doubling of capacity that reduces the specific cost by a factor of $2^{-b}$. Other applications may require a lower or higher scaling of capacity or knowledge gained, and that may influence the trajectory of the outcomes.

This analysis of endogenous technological learning in a bottom-up theoretical and analytical energy system model opens the door for several modifications and extensions. The assumption of a single world region, though inadequate for a thorough analysis of the interaction between regions on energy flow and technology transfer, still has many more technological details than most computable general equilibrium models. Tightly knitted to this is the consideration of technology spillovers. We are quite optimistic because spillovers across the globe are idealized. Another limitation of this study is that the technologies have been grossly aggregated. Although we emphasize electricity technology, the base reference energy system has several other technologies including conversion-based technologies that informed the total primary energy supply curves. The aggregation of technologies into a cluster with umbrella specifications prevents *modeling adequacy* particularly aimed at achieving a faithful representation of the optimal energy technology mix and landscape. Finally, it is imperative to note that the model parameters hold the potential to influence the outcomes. For example, in this analysis, we sample from a log-normal probability distribution function for the progress ratios of the technologies. While

[14]For example, learning differs in service industries like retail banking or shipping from automobile manufacturing and computer hardware.

[15]For example, while the textile and automotive industries have largely been incremental due to dominant design, the pharmaceutical industry has been competence-enhancing due to new drug discoveries.

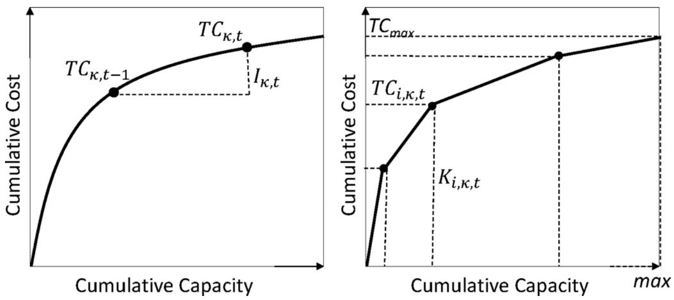


Fig. 13. Left panel shows the cumulative cost curve. The right panel shows the piecewise linear segmentation equivalent.

an analysis of the outcomes under other relevant distributions may present elements of robustness, we infer that they will be no more informative than the solutions we have presented here.

Other pertinent questions range from addressing how the results may be influenced by varying stabilization scenarios, knowing the impacts of other market and nonmarket-based policies on outcomes. These perspectives highlight some interesting extensions to this model. Moreover, the discussion on the effects of uncertainties in crafting an optimal energy technology policy is dynamic and thus, this topic will always be open for future analysis.

## Appendix

### A. Segmentation Procedure

We adopt the segmentation procedure in [5] such that for each realization of the uncertain learning elasticity, $b_\kappa\,(\omega)$, the total cumulative cost function in (5) is used to get the investment costs per period for each technology as

$$I_{\kappa,t}(K_{\kappa,t}) = \frac{a}{1-b_\kappa}\left(K_{\kappa,t}^{1-b_\kappa} - K_{\kappa,t-1}^{1-b_\kappa}\right) \tag{16}$$

We provide, exogenously, the maximum cumulative capacity as an upper bound for the capacity of the technology, and this is fed into the total cost per technology by time as $TC_{\max,\kappa,t} = \frac{aK_{\max,\kappa,t}^{1-b_\kappa}}{1-b_\kappa}$.

Also, we specify the number of segments, $s$, for the cumulative cost curve. This is the number of integer variables per technology and per period. The starting and final points of the curve and the number of segments are used to define the breakpoints or *kinks* of the curve using (7), see Fig. 13. The cumulative capacities are are calculated as $K_{i,\kappa,t} = (\frac{1-b_\kappa}{a}\mathrm{TC}_{i,\kappa,t})^{\frac{1}{1-b_\kappa}}$. The interpolation procedure follows from [42] and [55] by using binary variables to represent points on the piecewise curve as convex combinations of adjacent knots in the curve. This allows the description of the stepwise function as an equivalent of several linear constraints in a mixed integer program model. The cumulative capacity is the sum of the segments defined by $\lambda_{i,\kappa,t}$ by technology and by time, $C_{\kappa,t}(K_{\kappa,t}) = \sum_{i=1}^{s}\lambda_{i,\kappa,t}$. The cumulative cost is expressed as a linear combination of segments expressed in terms of the continuous $\lambda$ and binary $\delta$ variables,

$$TC_{\kappa,t} = \sum_{i=1}^{s}\alpha_{i,\kappa}\delta_{i,\kappa,t} + \beta_{i,\kappa}\lambda_{i,\kappa,t} \text{ and } \delta_{i,\kappa,t}\in\{0,1\} \tag{17}$$

There is only one active linear segment between $i=1$ to $s$, and it is captured by having only one $\delta_{i,\kappa,t}$ to be nonzero across all possible segments. The slope of each segment is the coefficient $\beta_{i,\kappa}$, and it is defined as

$$\beta_{i,\kappa} = \frac{\mathrm{TC}_{i,\kappa,t} - \mathrm{TC}_{i-1,\kappa,t}}{K_{i,\kappa,t} - K_{i-1,\kappa,t}}. \tag{18}$$

The intercept on the cumulative cost axis, $\alpha_{i,\kappa}$, for each segment is

$$\alpha_{i,\kappa} = \mathrm{TC}_{i,\kappa,t} - \beta_{i,\kappa}K_{i-1,\kappa}. \tag{19}$$

Additional constraints on the cumulative cost curve segment that is active are defined using the binary $\delta$ variables

$$\lambda_{i,\kappa,t} \ge K_{i,\kappa}\delta_{i,\kappa,t} \quad\text{and}\quad \lambda_{i-1,\kappa,t} \le K_{i,\kappa}\delta_{i-1,\kappa,t}. \tag{20}$$

This ensures that there is a $\lambda$ linking two successive cumulative capacity points ($K_{i-1,\kappa,t}$ and $K_{i,\kappa,t}$). The $\delta$ variables sum to 1 to ensure that only one binary variable is active each period, $\sum_{i=1}^{s}\delta_{i,\kappa,t} = 1$.

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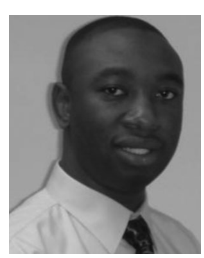

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