Inter-temporal R&D and Capital Investment Portfolios for the Electricity Industry's Low Carbon Future

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ABSTRACT

A pressing question facing policy makers today in developing a long-term strategy to manage carbon emissions from the electric power sector is how to appropriately balance investment in R&D for driving innovation in emerging low- and zero-carbon technologies with investment in commercially available technologies for meeting existing energy needs. Likewise, policy makers need to determine how to allocate limited funding across multiple technologies. Unfortunately, existing modeling tools to study these questions lack a realistic representation of electric power system operations, the innovation process, or both. In this paper, we present a new modeling framework for long-term R&D and electricity generation capacity planning that combines an economic representation of endogenous non-linear technical change with a detailed representation of the power system. The model captures the complementary nature of technologies in the power sector; physical integration constraints of the system; and the opportunity to build new knowledge capital as a non-linear function of R&D and accumulated knowledge, reflective of the diminishing marginal returns to research inherent in the energy innovation process. Through a series of numerical experiments and sensitivity analyses—with and without carbon policy—we show how using frameworks that do not incorporate these features can over- or under-estimate the value of different emerging technologies, and potentially misrepresent the cost-effectiveness of R&D opportunities.

Keywords: Electricity generation capacity planning, Energy R&D portfolios, Energy innovation, Endogenous technical change

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1. INTRODUCTION

Effectively managing carbon dioxide (CO_2) emissions from fossil-based electric power generation is critical for implementing a comprehensive global climate change mitigation strategy

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and sustainable energy plan. In the United States, for example, the electric power generation sector is responsible for approximately forty percent of the country's annual emissions (EIA 2014). Unfortunately, many technologies for significantly reducing CO_2 emissions from the electricity sector are either in early conceptual stages or are only available at relatively high costs or small scales, requiring additional research and development (R&D). Meanwhile, the industry continues to meet electricity demand with carbon-emitting technologies that are both commercially available and economically viable. To address the dilemma of resolving the need for new electricity supply with emission reduction goals, policy makers are searching for cost-effective investment portfolios for R&D in emerging electricity technologies and new generation capacity at the utility or power producer level (DOE 2015). On one hand, incentivizing existing low-carbon technology adoption can play an important role in near-term carbon reductions. On the other hand, supporting R&D can benefit long-term carbon reductions by commercializing new, less expensive low-carbon technologies for the future. What is the right balance between, and timing for, these two efforts?

Existing models used to support these decisions are limited in scope in that they either represent the power sector well or the process of technical change with additional scrutiny, but not both. Yet, we know from the long-standing research efforts of both the power sector modeling and innovation modeling communities that each of these sub-systems has several layers of operational and process-level details that are important when developing conclusions for policy decision support. There are multiple pathways through which technical change happens, and models of the energy innovation process have been endogenizing these pathways with increasing rigor. The electric power system is a complex sociotechnical machine; electricity models used by utilities, governments, and other stakeholders have become very sophisticated in capturing essential details about resource availability and power flow, and their impact on long-term capacity planning.

In this paper, we explore socially optimal low-carbon joint R&D and capital investment portfolios for the electric power generation sector, using a model with endogenous non-linear R&D and a detailed representation of the power system. We present a new integrated modeling approach that considers the complementary roles that generation technologies play within the power system, the physical integration constraints they face, and the economics at play in electric utilities' least-cost investment decisions. Specifically, the model uses a combination of electricity demand in multiple time-slices for the year, and the engineering costs and operating constraints of the electricity supply technologies to endogenously choose the cost-effective portfolio of generation capacity at a given time. In contrast, simple coarse representations of the power sector often use capacity factors and a pre-determined merit order for each supply technology to exogenously capture aggregate annual production. Our model also considers specific characteristics of the innovation process, including the opportunity to build new knowledge capital as a non-linear function of R&D investments and the current state of technical knowledge. The model explicitly represents the diminishing marginal returns to research that is inherent in the energy innovation process, as well.

A set of numerical experiments and sensitivity analyses is used to illustrate the impact of adding these features on the optimal R&D and capacity investment portfolio. Results show that exclusion of key technology characteristics and electricity system operational details can cause under- or over-estimating the cost-effectiveness of R&D investments. The role of solar is highlighted, whereby the benefit of solar R&D investment can be understated if its niche role to provide power during specific segments of the day is not represented. Likewise, the role of baseload technologies such as coal with CCS or nuclear is shown to be highly sensitive to the inclusion or exclusion of specific technology-specific operating constraints (e.g., ramp rates) relative to each other. We also show that introducing diminishing marginal returns to R&D translates into higher optimal R&D investments when compared to models that ignore this inherent characteristic of innovation. Overall, results expose the interaction between R&D and capacity deployment: the benefit of R&D investment is realized once a technology is deployed and supplying electricity at a lower cost than the alternate technology that would generate electricity in its place.

The remainder of this paper is organized as follows. Section 2 provides a review of the existing literature related to optimal R&D and capacity investment planning in the electricity generation sector, focusing on the subset of models that study joint R&D and capacity portfolios. Section 3 formulates the specific investment problem we seek to solve, and describes the structure and calibration of the new modeling approach. Section 4 presents the results of the reference version of the model, and then compares them to results from a number of alternate models to illustrate the impact of our approach. Section 5 provides a discussion of the results and suggests future research directions.

2. LITERATURE REVIEW

Existing models to inform optimal low-carbon R&D and capital investment portfolios for the electric power generation sector have characteristically excluded one of two critical aspects of the electricity industry and the energy R&D process that can provide useful insight to policy makers—an explicit, detailed engineering cost representation of the power generation sector or a detailed endogenous representation of R&D and the energy innovation process. Although there is considerable literature on both detailed engineering models of the power sector and on economic models of technical change, models for jointly studying capacity and R&D portfolios are few and still require fundamental improvements.[1] Online Appendix A summarizes this general dichotomy by listing the features of many well-known studies and models used to inform policy in this area.

First, models in this area can lack detail about the critical structure of, and engineering constraints within, the electric power system. The necessary cooperation between highly complex, time-dependent technical operations and the infrastructure itself sets electricity apart from other large-scale, commodity-delivering infrastructure systems. This feature requires a diverse portfolio of generating technologies during any given period of time in the system to complement one another to deliver reliable electricity. Research is underway to integrate more engineering detail into economic modeling frameworks (e.g., Tapia-Ahumada, Octaviano, Rausch, & Pérez-Arriaga 2014; Shawhan et al. 2014), but the typical approach for studying the energy R&D and capital investment planning problem thus far still uses a "top-down" economic perspective (e.g., Goulder & Schneider 1999; van der Zwaan, Gerlagh, Klaassen, & Schrattenholzer 2002; Buonanno, Carraro, & Galeotti 2003; Popp 2004; Popp 2006; Nordhaus 2010; Pugh et al. 2011; Hartley et al. 2016). Top-down economic models use either general equilibrium or inter-temporal optimal growth frameworks, and while they can be very useful for capturing economic feedbacks between sectors and for describing the impact of price changes, they lack detail about technology types; disaggregated capital, variable, and other fixed costs; physical operational constraints (e.g., solar and wind variability, nuclear plant cycling); and other important dynamics of the sectors and industries they represent. In addition, these models typically represent large aggregate time-steps, such as annual energy demand, without any information on inter-annual variability. For the electric power sector, this does not allow for

1. See Santen (2012) Chapter 3 for a comprehensive review of state-of-the-art electricity generation capacity planning models, state-of-the-art energy-economy models incorporating technological change, and models used for joint capacity and R&D planning. For brevity, we focus the literature review on the final of these.

generation technology expansion decisions to account for how different technologies within the system complement and interact with each other. For example, technologies that cannot cycle quickly or cost-effectively, such as coal or nuclear generation, are complemented by technologies that can efficiently cycle, such as natural gas turbines. A model that represents these technologies as competing on aggregated costs to provide annual energy services will miss these critical interactions.

Conversely, studies that represent engineering details of the power system typically omit an explicit endogenous detailed representation of the energy R&D process. While these models can rigorously capture technology-specific costs, temporal variability in power supply and demand, intermittency of renewable resources, and physical constraints of the system, due to data and other limitations most existing models for electricity investment portfolio planning rely on exogenous time trends or experience curves to represent the change in costs of different technologies over time, neglecting the explicit role of R&D (e.g., Short et al. 2011; Ross 2008; Grubb, Kohler, and Anderson 2002; Messner 1997; Mattheson & Wene 1997; Loulou, Goldstein, & Noble 2004; EIA 2009; Seebregts et al. 1999; Berglund & Soderholm 2006; Kypreos & Barreto 2000).

Models that incorporate both the technological details of the electricity sector and the key features of the innovation process are relatively rare, and they use a few different approaches. Some that have combined electricity sector engineering cost details and endogenous R&D assume linear (or one-to-one) relationships between R&D investment decisions and new knowledge creation (e.g., Kouvaritakis, Soria, & Isoard 2000; Turton & Barreto 2004; Barreto & Kypreos 2004; Miketa & Schrattenhozler 2004). While these models help address the shortfalls of status-quo models as described above, a linear approach does not capture diminishing marginal returns inherent to the research process for which there is empirical evidence and theoretical support. The functional form of the returns to R&D is a critical assumption, because empirical studies suggest that the state of scientific knowledge significantly affects the overall outcome of the R&D investment at a given point in time (Popp, Newell, & Jaffe 2010; Popp 2002).

Other models have targeted adding technological details of the power sector alongside key features of the innovation process using a "hybrid" approach, which aim to link engineering-cost and economic models in order to capture the full range of specifications needed to inform policy (e.g., Manne, Mendelsohn, & Richels 1995; Bosetti, Carraro, Galeotti, Massetti, & Tavoni 2006). For example, Bosetti et al. (2006) assumes a non-linear functional form for returns to R&D that exhibits diminishing returns within an energy planning model. However, this study and other similar hybrid modeling efforts still rely on relatively coarse resolutions for specific aspects of their electricity sector representations. Examples include accounting for multiple technologies but prescribing exogenous operational details, and integrating detailed costs but omitting inter-annual variability in demand.

Finally, recent studies have emerged that investigate the role of uncertainty in R&D with respect to electricity sector technologies (e.g., Blanford 2009; Baker and Solak 2011; Ybema et al. 1998; Bosetti & Tavoni 2009; Kypreos & Barreto 2000; Messner et al. 1995; Grubb 2002; Grubler & Gritsevskii 1997; Webster et al. 2015). For example, Blanford (2009) explores R&D investment strategies for the power sector under plausible alternative technological change pathways using an electricity model with engineering details and a stochastically structured R&D module. Bosetti & Tavoni (2009) develop a stochastic version of a hybrid energy and R&D planning model to consider uncertainty about the effectiveness of R&D programs. Baker and Solak (2011) present a stochastic top-down economic modeling framework to study optimal electricity R&D investment portfolios under endogenous technological change uncertainties. Webster et al. (2015) construct a top-down stochastic model of the climate and economy studying R&D portfolios into two substitutable backstop technologies under R&D uncertainties. While these studies raise the important question about the role of uncertainty in R&D planning for the electric power generation sector, each model still makes the practical trade-off of using limited details in either the representation of the innovation process or in the representation of power system operations to focus on the role of uncertainty.

The framework presented in this paper contributes to the literature by considering the economic details of the innovation process and the engineering details of the power system within a single, integrated model to study joint portfolios of R&D and generation capacity investment. It includes a state-of-the-art learning-by-searching process that represents endogenous non-linear R&D effects with diminishing returns, and also includes power sector operational constraints and interannual variability in demand and renewable generation. The contribution of this research is primarily methodological, and includes a stepwise discussion of the impact each of these details has on optimal inter-temporal R&D and capacity portfolios to further the dialogue on the value of incorporating these features into models to inform policy.

3. MODELING FRAMEWORK

We begin with a traditional engineering cost-based electricity generation capacity expansion optimization model (e.g., Turvey & Andersen 1997; Hobbs 1995) with ten technology categories, and modify it to simultaneously choose R&D investments for four emerging low-carbon technologies: coal with carbon capture and sequestration (coal with CCS), nuclear, wind, and solar.[2] The model includes technology specific costs; temporal load variability; and engineering constraints governing the power balance, supply reliability, intermittent wind and solar power, and constraints on cycling nuclear generators. We build upon previous modeling work in the literature that incorporates both endogenous experience curves and endogenous R&D dynamics to allow overnight capital costs to evolve as a function of capital investments and technological innovation (e.g., Barreto & Kypreos 2004; Fischer & Newell 2008). However, the new model of the innovation process exhibits diminishing returns with increasing research effort (e.g., Popp 2004; Popp 2006; Bosetti et al. 2006). The planning horizon is sixty years, with capital investment and R&D investment decisions made every five years. A centralized planning approach is used, which assumes that a central decision maker simultaneously makes national investment and generation decisions. This centralized approach is appropriate for the type of long-range strategic policy and technology-planning that our method is intended to address. For this class of long-term planning studies, it is not necessarily relevant or useful to represent individual firms because of the large structural uncertainties inherent in short-term market behaviors of individual firms over these time scales (Pérez-Arriaga & Meseguer 1997). Below, we present the key features of the model, data, calibration, and solution approach. Full model details are provided in Online Appendix B.[3]

3.1 Objective

Every five years, the decision maker chooses new power plant capacities, $NC_{g,t}$, for each technology g, and R&D investments, $RD_{g,t}$, for the subset of emerging technologies, to minimize the net present value of total system costs,

2. We refer to the "optimal" investment strategy here, and throughout the remainder of the paper, in reference to our numerical implementation of the investment problem rather than to an "absolute" optimum.

3. For the purpose of presentation, the equations shown below are in some cases condensed versions of the fully detailed model in the Appendix.

Table 1: Electricity Generator Data

Tech	Initial Capacity	Heat Rate	Initial Capital Cost	Fixed O&M Cost	Initial Fuel Cost	Other Variable Cost	Annual Availability
Old Coal	300	10.00	1204	23.410	2.28	4.14	85
New Coal	1	8.80	3167	35.970	2.28	4.25	85
Coal with CCS	1	12.00	5099	76.620	2.28	9.05	80
Old Steam Gas	100	9.46	390	25.256	5.16	3.85	80
Gas Combined Cycle	200	6.43	1003	14.620	5.16	3.11	90
Gas Combustion Turbine	100	9.75	665	6.700	5.16	9.87	90
Hydro	100	10.34	1320	12.700	—	3.20	90
Nuclear	100	10.40	5355	85.663	0.62	0.48	90
Wind	50	—	2438	28.070	—	—	30
Solar	1	—	4755	16.700	—	—	95[a]

[a] The availability rate for solar is high due to the technology only operating during peak solar demand slices.
Units: Initial Capacity is in GW. Heat Rate is in MMBtu/MWh. Initial Capital Cost is in $/kW-knowledge unit. Fixed O&M Cost is in $/kW-year. Initial Fuel Cost is in $/MMBtu. Other Variable Cost is in $/MWh. Annual Availability is in %.
References: Short et al., 2011; EIA, 2010a; EIA, 2010b

$$\min_{NC_{g,t},RD_{g,t}} \sum_{g,t}^{G,T} [(FC_{g,t} + VC_{g,t} + RD_{g,t}](1+r)^{-t} \tag{1}$$

where $FC_{g,t}$ represents the total fixed costs (overnight capital and fixed O&M costs) of technology category g in period t, $VC_{g,t,}$ represents the total variable costs (fuel and variable O&M costs) of technology g in period $t,$ and r is the discount rate.

In addition to the constraints that define the design and operation of the underlying electric power system, summarized below, the key constraint driving the optimal investment strategy is a cumulative carbon emissions cap, *ecap*,

$$\sum_{t}^{T} E_t \leq ecap \tag{2}$$

where E_t represents total carbon emissions from the electricity sector during each period. The existence of a cumulative cap forces a choice between reducing emissions now versus later, given current technology costs and future R&D-based cost-reduction potential.

3.2 Electricity System Operations

We parameterize the power system model to be qualitatively representative of the U.S. generation portfolio and electricity demand (EIA 2014; Short et al. 2011). Table 1 lists the technology categories and associated values used for key parameters in the generation expansion problem. Electricity demand is characterized using an annual load duration curve with seventeen time slices representing four seasons, four daily segments within each season, and a "super peak" representing the highest forty (non-consecutive) hours of demand. Figure C1 in Online Appendix C shows the duration and power level associated with each segment of the load duration curve.[4]

4. Demand is represented in the model as inelastic, fixed at the level shown for each step in Figure C1.

Key constraints of the traditional power generation expansion planning and optimal dispatch problem are retained, including those dictating energy demand balance, reliability of supply, and energy resource availability. To this model, we introduce several additional details. First, we represent to first order the effects of intermittent renewable resources and the dominant operational constraints of nuclear power plants. Using a net-load approach, both solar power and nuclear power are defined as "non-dispatchable," and all other technologies compete on cost in order to meet demand. Wind is modeled as "dispatchable" and thus includes the possibility of curtailment. Solar power is also represented as operating only during demand slices that correspond to daytime hours. Second, a high retirement rate is used for old coal and old oil/gas steam plants, because a very large capacity of these technologies is expected to retire in the U.S. over the next one to two decades. A high retirement rate for nuclear power is also included, given the aging stock of the U.S. nuclear fleet. Conversely, new investments in old coal technology, old oil/gas steam, and hydropower are not allowed in the model because these technologies are outdated or near their energy resource limits in the U.S. Third, we represent the inability to scale up emerging technologies rapidly and without limit by assuming a constraint on the rate of change of installed capacities between periods. Tables C1–C3 in Online Appendix C show the values assumed for these growth rates and other system parameters.

It is important to note that there are many relationships and levels of detail that can be used to represent the engineering reality of the electric power system and its operations, and existing industry standard power system models have become very sophisticated in many regards. This can include describing the chronological dispatch of generators on an hourly basis; unit-commitment features of individual generators; geographic (meteorological) variability of wind and solar energy resources; heterogeneity in the electricity supply resource portfolios across different regions; the impact of congestion and other transmission constraints; and the different incentives and competitive conditions electric utilities face in different market structures across the U.S. The balance of features represented within a specific model typically matches the planning horizon of the problem. For tractability, medium-term models (up to one year) tend to represent detailed security-constrained unit commitment and hourly chronological dispatch but not capacity expansion. Longer range planning models (10–50 + years) will include capacity and transmission expansion, and geographic variation, but not hourly chronological dispatch or unit commitment. At present, models that include both detailed operations and hourly chronological dispatch alongside capacity expansion are rare, and those that exist tend to rely on simplified representations of unit commitment and network operations, and represent time through snapshot days or weeks in order to keep computer run times manageable.

The main objective of this paper is to investigate how the integration of power system and innovation process details into a single framework to study the joint R&D and capacity investment problem for the electricity sector results in different investment strategies from when these features are not considered. Thus, to keep the insights clear, we use a model that is as simple as possible with the minimum amount of added realities, and study whether even this level of introduction makes a non-negligible difference. Because simplifications such as the use of time slices to represent annual demand, aggregation of individual generating units into technology groups, and prescription of dispatchable versus "must-run" technologies can introduce bias in operations (and therefore optimal future investments) by making resources appear more or less productive than they actually are, we discuss the sensitivity of our results and impacts of other model structures. However, we leave the full integration of the new framework into models with higher temporal and spatial resolution to future research.

3.3 Technical Change Dynamics

The innovation process is represented in the model through two distinct complementary pathways. Building on the recent empirical and numerical modeling literature, we use a two-factor learning curve (2FLC) to simultaneously represent learning-by-doing (LBD) and learning-by-searching (LBS) (e.g., Klaassen, Miketa, Larsen, & Sundqvist 2005; Soderholm & Klaassen 2007; Miketa & Schrattenholzer 2004; Barreto & Kypreos 2004; Jamasb 2007). Through the 2FLCs, the overnight capital cost of a technology decreases in the technical knowledge stock for the technology, and also decreases in the cumulative capacity installed. While the 2FLC formulation applies to the emerging technology groups (coal with CCS, nuclear, wind, and solar), all technologies for which new capacity can be added continue to learn via LBD implemented with a traditional one-factor learning curve.

The technical change dynamics in the model are summarized with the following three equations:

$$NEWK_{g,t} = \alpha_g RD^{\beta}_{g,t} KS^{\phi}_{g,t} \tag{3}$$

$$C_{g,t} = \frac{C_{g,0}}{(IC^{\eta 1_g}_{g,t})(KS^{\eta 2_g}_{g,t})} \tag{4}$$

$$KS_{g,t+1} = NEWK_{g,t} + \delta_g KS_{g,t} \tag{5}$$

Equation (3) represents the production of new knowledge, $NEWK_{g,t,}$ for technology g in time period t, defining it as a function of R&D investment, $RD_{g,t}$, and the cumulative technical knowledge stock, $KS_{g,t}$, for technology g in time period t. The parameter β_g represents the contribution of R&D dollars invested in the creation of new knowledge, φ_g represents the contribution of the current knowledge stock in the creation of new knowledge, and α_g is a technology-specific scalar used to calibrate the behavior of the new innovation possibilities frontier to the current learning literature. Diminishing returns to research are incorporated in this "innovation possibilities frontier (IPF)," by constraining the sum of $\beta_{g,}$ and φ_g to less than 1.0.

Equation (4) represents the two-factor learning curve that combines LBD and LBS. $C_{g,t}$ is the capital cost of technology g in time period t, $C_{g,0}$ is the initial capital cost at unit capacity and knowledge stock, $IC_{g,t}$ is the cumulative installed capacity in GW of technology g in time period t, $KS_{g,t}$ is once again the cumulative knowledge stock for technology g in time period t, and $\eta 1_g$ and $\eta 2_g$ are the learning-by-doing and learning-by-research output elasticities for technology g, respectively. As indicated by the subscript g, the parameters $\eta 1_g$ and $\eta 2_g$ are technology specific; their interpretation follows directly from traditional experience curve "progress-ratio" calculations where $1–2^{\eta i}$ describes the cost reduction that occurs from a doubling of capital stock ($\eta 1$) or knowledge stock ($\eta 2$) (e.g., Ibenholt 2002). For the non-emerging technology groups, $\eta 2_g$ is set to zero, resulting in one factor LBD curves driving reductions in overnight capital costs.[5] Technology-specific parameters of the IPF and 2FLC, listed in Table 2, are calibrated to estimates in the published literature. Specifically, the scaling parameter, α_g, minimizes the sum of squared differences between capital cost reductions as formulated here, and capital cost reductions based on published

5. For consistency, one-factor LBD parameter values were re-constructed from the 2FLC values employed by Barreto & Kypreos (2004), based on achieving the same cost-reduction over capital stocks.

Table 2: Reference Model Technical Change Parameters

Technology	Learning-by-Doing Elasticity η1	Learning-by-Searching Elasticity η2	IPF a	IPF β	IPF ϕ
Coal with CCS[a]	0.05889	0.02915	0.1853	0.1	0.54
Nuclear	0.05889	0.02915	0.1853	0.1	0.54
Wind	0.25154	0.10470	0.1856	0.1	0.54
Solar	0.41504	0.15200	0.1760	0.1	0.54

Original Sources: Barreto & Kypreos 2004; Popp 2006

[a] The lack of historical experience with carbon capture and sequestration technology in the electric power sector makes it difficult to find reliable learning data for use in numerical models of technological change. Other authors have used learning rates for coal SO_2 scrubbing technology or NO_x reduction technologies and applied them to coal with CCS technology in numerical decision support models (e.g., Rubin, Taylor, Yeh, & Hounshell 2004). This paper uses the history of nuclear fission technology and its learning rates as a proxy for coal with CCS (both are capital-intensive, large baseload technologies with significant challenges to space, scale up, public acceptance, permitting, waste, etc.).

two-factor LBD and LBS rates, and R&D and knowledge stock output elasticities (Barreto & Kypreos 2004; Popp 2006). Equation (5) represents the knowledge building process, capturing the stock nature of knowledge capital. The parameter $NEWK_{g,t}$ represents the new knowledge gained for technology g during period t through the innovation possibilities frontier, and δ_g represents a technology-specific decay rate for the knowledge stock from one period to the next.

Several caveats are worth stating. The wide range of estimates in the published literature on learning rates, existing debate on the appropriateness of using historical data to estimate future costs for emerging technologies, and specification challenges of including endogenous technological change curves in optimization models are issues that have previously been documented (e.g., Nordhaus 2014; Anadon et al., 2014). Additionally, LBS and LBD are just two of many possible pathways of technical change; spillovers, learning-by-interacting, and exogenous economy-wide innovation represent additional important pathways. Comprehensively incorporating the full range of pathways for change is beyond the scope of this paper. However, we acknowledge that these additional mechanisms exist, and can impact the specific numerical results presented here. Following the presentation of results, we return to this issue and provide a discussion.

3.4 Numerical Implementation

We solve the electricity generation capital and R&D investment planning problem numerically, as a non-linear program. We use the GAMS modeling environment, and a standard non-linear programming (NLP) solver, CONOPT. A 20-point seeding algorithm is also used to set initial values widely distributed over the solution space. The optimum is the solution to the NLP that minimizes total system costs across all twenty seeds. We address terminal conditions for this multi-period decision problem by running the 60-year planning problem for an additional 40 years. Results from only the first 12 (5-year) periods are used in each of the analyses to ensure that decisions being made at or near the end of the planning horizon are not "end-of-world" artifacts or a result of artificially imposed terminal conditions.

4. RESULTS

In this section, we present results from three numerical modeling experiments, and summarize a series of related sensitivity analyses. As described above, the reference model includes four "emerging" technologies—wind, solar, coal with CCS, and nuclear—each with a distinct engineering cost structure (e.g., fuel costs, initial capital costs) and learning potentials as shown in Tables 1 and 2. It is the interaction of the cost structure, cost-reduction potentials, carbon reduction potential, and role of each emerging technology within the power system that determines the optimal R&D and capacity investment strategies. We first present the optimal investment strategy from the reference model with no carbon limit and then with a stringent cumulative carbon limit equivalent to reducing 2010 business-as-usual carbon emissions from the power generation sector by fifty percent annually.[6,7] In the subsequent sections, we present how the R&D and capacity investment portfolio changes when we change how the power system or the innovation process is represented in the modeling framework.

4.1 Reference Optimal Investment Strategy

When carbon emissions from the power generation sector are allowed to grow unconstrained, the new modeling framework with endogenous R&D-based technical change and diminishing returns shows that it is optimal in the near-term to invest aggressively in wind R&D, to a lesser extent in solar PV R&D, and then to decrease investments in both technologies to a negligible amount after twenty to forty years (Figure 1a). The temporal pattern of optimal capacity investments (deployment) for the reference model (Figure 2a) helps explain this behavior. Several gigawatts of wind are installed in the second and third periods in order to make up a sizeable share of the total installed capacity by the fourth period. R&D investments reflect this deployment pattern as the decision is driven by the benefit of the investment, realized when a technology is deployed. R&D investments occur early and aggressively to reduce costs as much as possible before massive deployments. Solar PV deployments in years 25 through 45 occur on a much smaller scale, but solar R&D investments similarly reflect capacity increases over time. Investments begin early in order to reduce capital costs as much as possible (although to a lesser extent than for wind), and they occur over a longer interval of time because deployments occur further in the future.

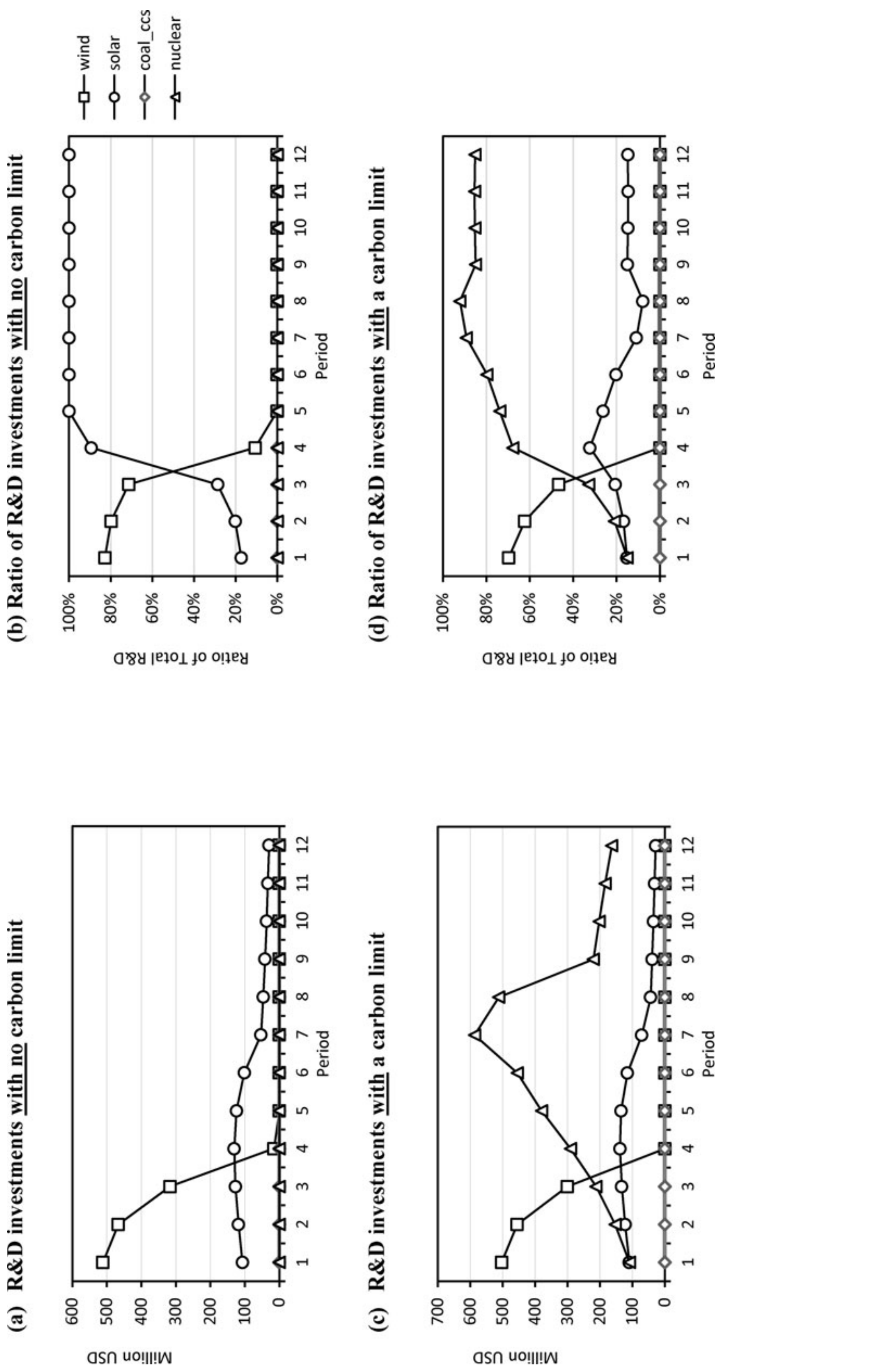
Note that wind and solar PV technology R&D and deployments appear even in the absence of a carbon emissions limit; this is due to their particular cost structures and the presence of learning in the model. Wind technology is already close to being cost-competitive with the other technologies' capital costs. Because of its competitive cost and relatively rapid learning rate, near-term R&D investments and deployment in wind yields significant cost savings during future installations, which in turn encourages further deployment.[8,9] Solar PV technology, despite significantly higher

6. A 50% reduction is equivalent to an average of 1000 million metric tons CO_2 reduction per year, which corresponds to an approximately $40/metric ton carbon price in 2010 and $10–15/metric ton carbon price in 2050 (due to path dependent and technology advancement effects). All dollars are expressed as 2005$. Source: Morris, J., Paltsev, S., and J. Reilly (2008), "Marginal Abatement Costs and Marginal Welfare Costs for Greenhouse Gas Emissions Reductions: Results from the EPPA Model," MIT Joint Program on the Science and Policy of Global Change Report No. 164, November 2008.

7. Variation in carbon limit stringency was tested, with 25-percent and 75-percent below business-as-usual scenarios also. Results were qualitatively similar to the median 50-percent reduction scenario with the same technologies being selected for R&D and capacity investments, and magnitudes decreasing (or increasing) monotonically with decreasing (or increasing) stringency. We therefore present results from the 50-percent scenario as representative of a carbon limit.

8. When engineering details of power system operations and merit-order effects are considered in combination with endogenous learning opportunities, as in the current modeling framework, it is not uncommon to witness significant wind technology deployment. Fuel costs are zero, other variable costs are among the lowest in the technology suite, and overnight capital costs become low due to cumulative LBD, LBS, and other effects). In our results, the amount of wind (or any other technology) R&D and deployment can also be attributed to previous technology support policies such as a production tax credit or state RPS since implicit in the learning rates, and thus costs, is the effect of past installations motivated by these policies. Note, however, that technology capital costs do not directly reflect the impact of such support policies.

Figure 1: Reference Model Optimal R&D Investments



capital costs compared with other technologies, is also developed and deployed due to its high learning potential (both through experience and R&D). In contrast, low-carbon coal with CCS and carbon-free nuclear, both technologies with relatively high overnight capital costs but lower learning potentials, do not have sufficient incentive for either R&D or deployment in the absence of a carbon constraint. Figure 1b shows the relative allocation of R&D for the optimal investment strategy in each period, and indicates the substantial early R&D investment in wind technology, followed by delayed, but prolonged investment in solar PV. For the remainder of the paper, we present the optimal R&D investment strategy in terms of the ratio of R&D by technology to the total R&D, and emphasize insights into the relative investment allocation, rather than the absolute magnitudes from our model.

Under a stringent carbon limit, one that is equivalent to constraining annual carbon emissions from the power generation sector to fifty percent of "business-as-usual" emissions (from 2010), the optimal strategy is to choose R&D and capital investments in nuclear technology, in addition to the same absolute wind and solar R&D and capital investments as with no carbon limit. Nuclear technology R&D investments occur more gradually than wind and solar, peaking after 35 years, just before new nuclear capital investments occur (Figures 1c and 2c). Because nuclear generation is baseload (operating for most hours of the year), emits no carbon, and has lower capital and operating costs than coal with CCS—the alternative baseload low carbon technology, it plays an important role in reducing cumulative carbon emissions. Note the significant amount of electricity generated by nuclear in Figure 2b under a carbon limit. However, the deployment of nuclear is deferred until later periods to take advantage of the capital cost reductions from early R&D investments. Under the carbon limit, nuclear technology has the largest share of R&D (Figure 1d). We note that neither R&D nor deployment of coal with CCS occurs in the optimal strategy for the reference model. This is a result of its higher overnight capital costs and fuel costs relative to alternative low-carbon technologies, a "must run" constraint imposed on substitutable baseload nuclear power in the model, and its relatively lower learning rates.[10] The specific role of coal with CCS is discussed again in Section 4.2 in more detail.

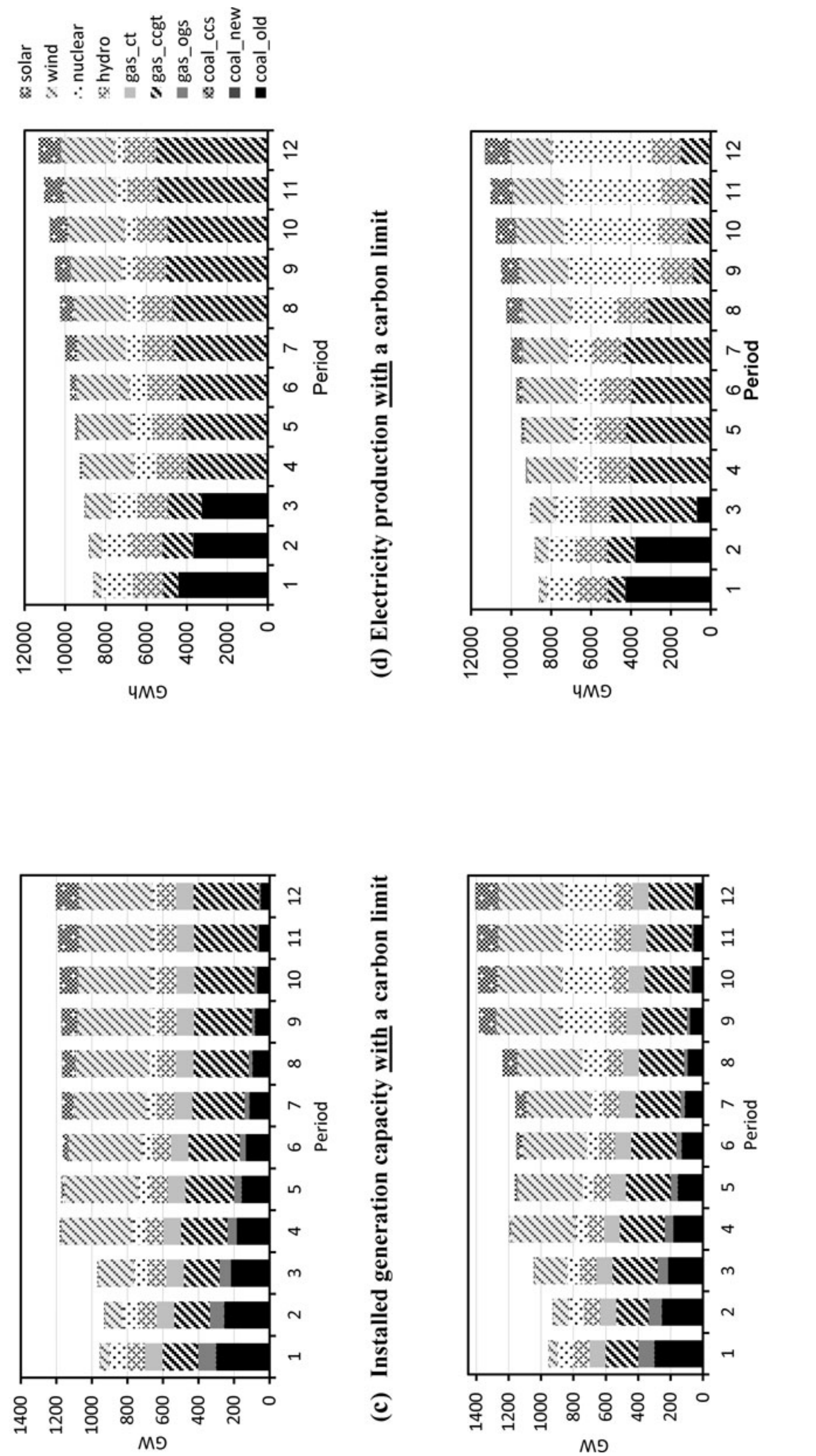
4.2 Effect of Power System Operational Constraints and Interannual Variability

The results described above are obtained using an engineering cost-based structure for the model instead of an economic modeling structure commonly used for joint R&D and capacity investment studies. The objective was to explore the effect of including operating constraints on generating technologies and of explicitly modeling variability within a year for demand, wind and solar availability, and their correlation with each other. In this section, we present results obtained with alternative formulations of the model with important engineering constraints changed to investigate whether and how the optimal investment strategy is different than the reference model's strategy.

9. While capital and other engineering costs for wind power decrease to the point of being cost-competitive with some conventional technologies, other constraints continue to exist (e.g., transmission capacity) that can prevent actual wind deployment, and these are not represented in our model.

10. The numerical model considers the possibility that coal with CCS and nuclear power technologies can incur an upper bound in deployment for political or physical reasons (e.g., concerns about nuclear waste disposal or public safety, physical limitation of carbon sequestration sites) by including a maximum installed capacity of 30% (for each) of total system capacity. However, neither constraint is active in the solution, indicating that the results are robust to these types of concerns within this limit.

Figure 2: Reference Model Optimal Installed Generation Capacity and Electricity Production



(a) Installed generation capacity with no carbon limit

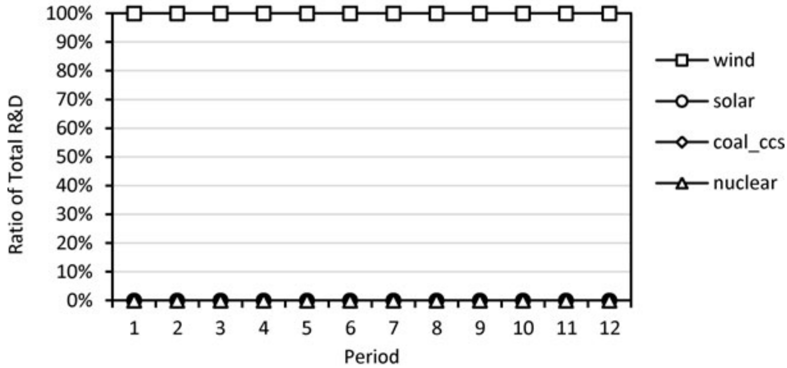
(b) Electricity production with no carbon limit

(c) Installed generation capacity with a carbon limit

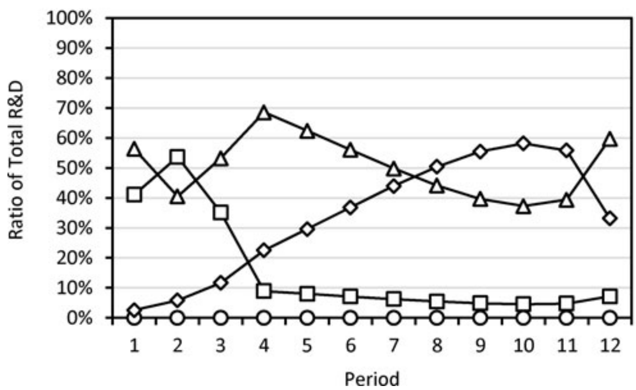
(d) Electricity production with a carbon limit

Figure 3: Ratio of Optimal R&D Investments to Total R&D Investments per Period without Power System Details Modeled

(a) No carbon limit



(b) Carbon limit

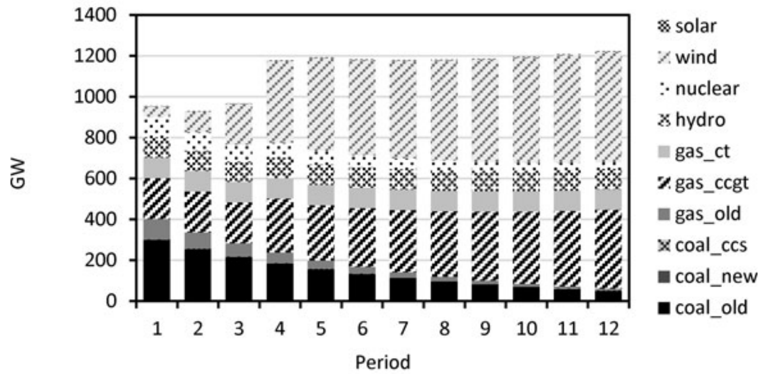


Using a "simplified" power system model, we neglect explicit representations of temporal load variability, time-of-day output constraints for solar PV, and the inability of nuclear plants to cost-effectively manage repeated start-up and shut-downs. We assume an average value for annual demand, solar PV output that assumes a fixed average annual capacity factor (30%) for all hours of the year, and neglect the baseload must-run constraint placed on nuclear power generation in the reference model. These assumptions are consistent with the way top-down economic energy models that focus on the rest of the economy represent a simplified electricity sector—using aggregate annual demands, operational details via technology-specific capacity factors or direct levelized costs (see Section 2), and perfect substitutability between technologies. In the simplified model, the endogenous non-linear innovation process is left in its original form from the reference model.

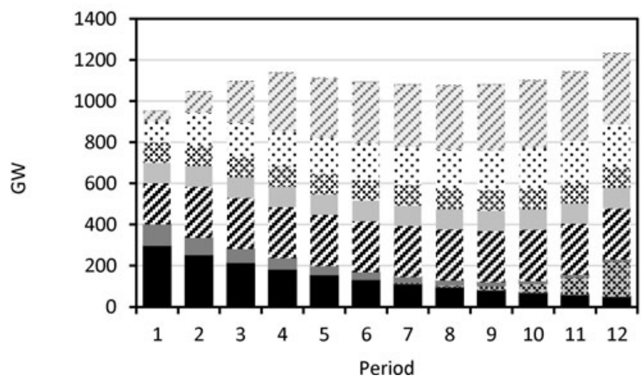
Figures 3 and 4 present the optimal R&D and capacity investments, respectively, from the simplified power system model. Without a carbon limit, the R&D investment strategy focuses solely on wind technology. R&D into solar PV technology is not part of the investment strategy, which differs significantly from the results obtained with the reference model. As expected, solar PV

Figure 4: Optimal Installed Capacities without Power System Details Modeled

(a) No carbon limit



(b) Carbon limit



technology is also dropped from the deployment plan, with wind making up the balance. With a carbon limit, R&D and capital investments in solar are effectively zero. Further, in contrast to the reference model, wind R&D investments continue throughout the sixty-year planning horizon. The simplified model's strategy also includes investment in both baseload low-carbon technologies, nuclear and coal with CCS. Investment in nuclear R&D is still optimal under the simplified model, and remains at a relatively high share throughout the planning horizon (instead of initially low and gradually increasing over time). However, the role of coal with CCS generation changes dramatically, with R&D and capital investments throughout the planning horizon. In fact, by the seventh period coal with CCS receives the largest share of R&D expenditures across the four emerging technologies.

Why are R&D investments in coal with CCS justified under a carbon limit in the simplified model, and how does this generalize across different conditions? One reason is the absence of the must-run constraint on nuclear generation. Without this constraint, both coal with CCS and nuclear compete on their cost merits to meet electricity demand. Nuclear generation, initially with lower overnight capital cost, is deployed sooner in the simplified model than in the reference model, and therefore calls for high R&D investment shares in early periods. Coal with CCS is initially higher cost, and is deployed in later periods after R&D investments have had sufficient time to reduce capital costs and increase its competitiveness. The R&D investment share in coal with CCS begins low in the early periods, and rises swiftly over the next few periods. This is due to the nature of the non-linear response of cost-reductions to increasing installed capacity and knowledge stock.

The reason why solar PV R&D is not included in the optimal strategy of the simplified power system model is because the model does not differentiate between the times when this technology is and is not available. Solar generation is assumed to be available at any time of day or in any season regardless of solar incidence, but only and always at 30% output, as opposed to the much higher levels for some seasons and times of day. A maximum capacity factor of 30% combined with its high initial capital cost, makes this technology cost-ineffective compared to other technologies (e.g., wind, natural gas). Solar technology is less valuable in the underlying generation resource portfolio when the correlation between demand and availability is not represented; the benefit of cost-reduction through R&D investments thus diminish, as well.

In addition to developing the simplified model, we also constructed a highly-detailed engineering operations model on a test-system, against which we compared results to a replica of the reference model on the same test-system. The objective of the test was to determine whether increasing the level of engineering detail further—in an effort to mimic state-of the-art power systems models—resulted in amplified and unidirectional changes to those seen when moving from the simplified model to the reference model. Online Appendix D provides a detailed discussion of this analysis. Overall, the test shows that common methods for designating technologies as "baseload" versus otherwise available need to be carefully considered in the context of defining relative positons of substitutable technologies. The analysis also highlights that keeping the relative positions of technologies with respect to satisfying demand in a given hour may likely be the more important driver in understanding cost-effective R&D investment opportunities than simply adding engineering reality. Understanding these positions further would be a valuable line for future research.

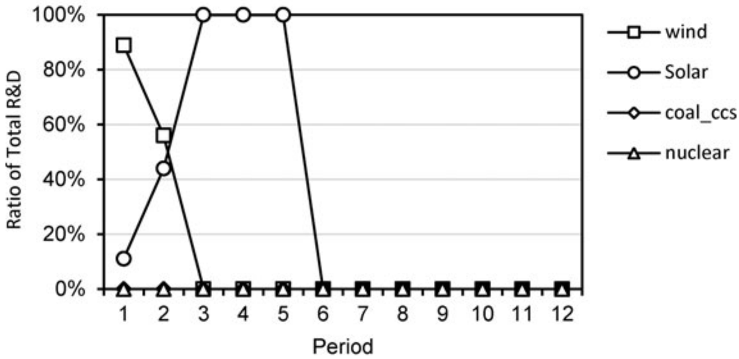
Overall, our results show that using economic modeling frameworks without a minimum level of temporal resolution to represent the variability inherent in renewables can underestimate the value of variable generation technologies such as solar PV in a resource portfolio, and therefore can also underestimate the cost-effectiveness of their R&D opportunities. For baseload technologies with specific engineering constraints such as nuclear and CCS, preserving their relative operating positions through a consistent set of constraints appears to be an additional important consideration for understanding the corresponding value of R&D investment into these technologies. As such, the numerical results caution against drawing premature conclusions about a specific direction for R&D investments with increasing modeling detail. Instead, they support a more general point that increasing the reality with which the power system is represented can indeed change the optimal investment strategy and priorities for certain technology over others.

4.3 Effect of Diminishing Returns to Research

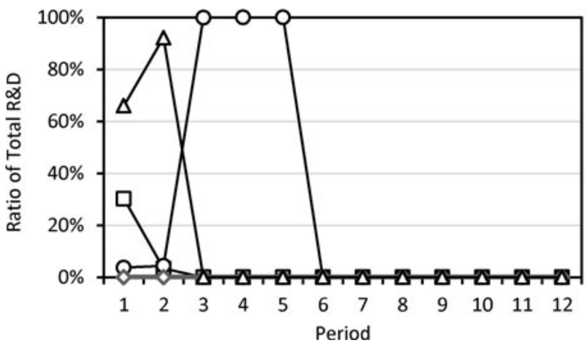
A second contribution of this work is the incorporation of diminishing returns to research into an R&D and capital investment planning model for the power sector. Here, we demonstrate the impact of representing this phenomenon, relative to an approach that assumes linear R&D-knowledge building relationships without diminishing returns, common in prior studies. We formulate a third version of the model, which replicates the reference version from Section 3.3 with an important change in the mechanism through which knowledge increases about emerging technologies. Specifically, in this version, we replace Equation (3) in the reference model with:

Figure 5: Optimal R&D Investments without Diminishing Returns to Research

(a) No carbon limit



(b) Carbon limit



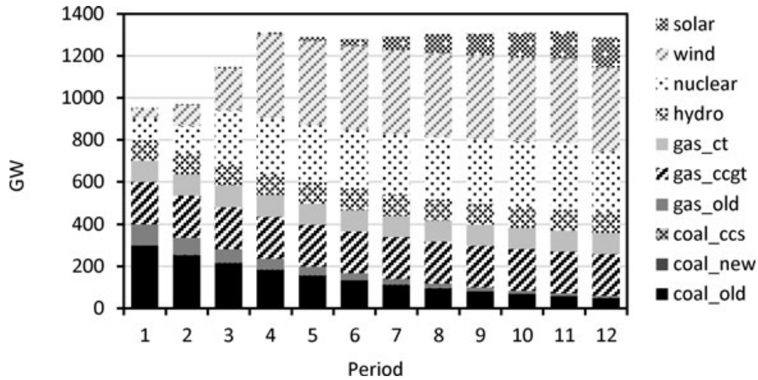
$$NEWK_{g,t} = RD_{g,t}, \tag{6}$$

where new knowledge, $NEWK_{g,t}$, for technology, g, in time, t, is a one-to-one function of the dollars invested in technology, g, and time, t. This formulation closely matches the dominant assumption in many energy models, which equates R&D dollars with new knowledge. We refer to this version as the “linear R&D” model.

Figure 5 shows the optimal R&D investment strategies with and without a carbon limit when the linear knowledge production function (6) is assumed, omitting diminishing returns. In the absence of a carbon limit, the relative shares of R&D investments into wind and solar PV in the early years is approximately the same as the shares of these technologies with diminishing returns, but R&D into solar ceases after the twenty-five years. The same pattern holds for wind and solar R&D investment under a carbon limit. In the linear R&D model, R&D into nuclear technology under the carbon limit has a higher optimal share in the first ten years, after which investment stops abruptly. In contrast, when diminishing returns are considered (Figure 1), nuclear R&D increases gradually, becoming the dominant R&D investment for most of the planning horizon.

In general, ignoring decreasing marginal returns from research overestimates the effect of R&D into technologies. The linear R&D model also chooses a different temporal path of optimal

Figure 6: Optimal Installed Capacities without Diminishing Returns to Research, under a Carbon Limit



R&D investments, leading to a "boom-and-bust" pattern of increased R&D in early periods, after which the R&D levels are zero. This is particularly true for technologies such as solar PV and nuclear, which are not deployed until later in the horizon and for which investment in the reference model is spread out over many periods. For technologies with low learning-by-searching rates but large capacity deployments in the reference model (e.g., nuclear under a carbon limit), the linear R&D model chooses a disproportionate level of R&D effort in the early periods. The shift in the timing of R&D in turn, tracks the optimal capital investment pattern, which includes earlier deployment of nuclear generation (Figure 6), displacing combined cycle natural gas plants during those periods. A similar pattern is seen for nuclear technology R&D investments under a carbon constraint in the engineering cost model of Barreto & Kypreos (2004), which assumes linear R&D-based knowledge building and the same low learning rate. In their model, technologies with higher learning rates witness continued R&D investment over the planning horizon.

As mentioned earlier in the text, we note that our implementation of the model includes only the learning-by-searching and learning-by-doing components of technical change, but that other important pathways for technology improvement and cost-reductions are in reality present. We would not expect the inclusion of an exogenous technical change rate to affect the insights from the current results, as the priority orders of R&D and capital investments for technologies are based on their competitive merits in relation to each other; the same cost reduction applied across all technologies would not change their competitive roles. However, inclusion of other pathways such as spillovers or learning-by-interaction could change the results more meaningfully. For example, if knowledge gained by improving component technologies to support integration of intermittent wind power can spillover to solar, the optimal strategy may include decreased R&D investment into solar, as the model sees less need for R&D for the same amount of absolute technical change. This is but one example of many that deserves more systematic study in future research efforts.

5. SENSITIVITY ANALYSES

Finally, in addition to exploring the effect of power system details and diminishing returns to research on the optimal investment strategy via the numerical experiments above, we performed a series of sensitivity analyses. A detailed description and discussion of each is provided in Online Appendix E.

The first sensitivity analysis explored the changes in the optimal investment strategy for different values of key innovation parameters: the impact on new knowledge from R&D expenditures and from the existing knowledge stock level. A benefit of representing endogenous learning-by-searching with an innovation possibilities frontier (IPF), such as Equation (3) of the reference model, is the ability to explicitly study assumptions about the effect of R&D efficiency (parameter β) and existing knowledge stock level efficiency (parameter ϕ) on the inter-temporal knowledge building process, and consequently on the optimal investment strategy. This is relevant in light of evidence in the empirical literature showing variation across energy technologies in the contribution of their knowledge stocks to successful innovation (Popp et al., 2013). When compared side-by-side, we conclude that the sensitivity of the optimal investment strategy in terms of relative R&D shares to both R&D investment and knowledge stock elasticities is similar in that for those technologies with high learning rates and early period R&D investments, the share of R&D investment tends to decrease (or stay constant) with increasing values for these parameters. On the other hand, for technologies with low learning rates (e.g., nuclear) and deferred R&D investments, the share of R&D investment tends to increase for higher values of these parameters. One noteworthy difference in the sensitivities however is that the impact of the knowledge stock elasticity is large enough to change the priority ordering of R&D investments under a carbon limit.

The second sensitivity analysis explored the effect of regional heterogeneity in the electricity supply base (including renewable resources) on the optimal investment strategy, comparing results from a small windy coal- and gas-heavy region and a much larger sunny, coal- and nuclear-heavy region to the national-level reference model results. The interpretation of R&D and technical change is more complex for a regional analysis. Knowledge gained from R&D or experience about these technologies is not likely to be contained within a region, so there is a limit to the value in determining "optimal" regional R&D allocations. Nevertheless, the focus of this sensitivity analysis is the adaptability of the modeling framework to the underlying characteristics of the electricity system represented, and the robustness of the temporal pattern of R&D priorities tracking the deployment needs of the underlying power system. Results show that under a carbon limit requiring large carbon emissions reductions, nuclear continues to play an important role in new capacity, and therefore increased R&D investments in nuclear are optimal in earlier periods. Additionally, we show that irrespective of climate policy, there is a reliance on a region's highest quality renewable energy resource, and preferential R&D investment in it.

6. CONCLUDING DISCUSSION

In this paper, we have presented a modeling framework for balancing investments in R&D and generation capacity infrastructure in the electric power sector. Specifically, the framework adds to the current state-of-the-art modeling in this area, which is predominantly top-down. We integrate an explicit bottom-up structure for representing important power system details, such as temporal load variability, technology-specific operational constraints, intermittent renewable generation, and technology-specific engineering and fuel costs, with a non-linear innovation possibilities frontier function for representing a process of knowledge building that captures the amount of R&D invested, the current state of knowledge, and diminishing returns.

In our new model, deployment via capacity investment for the most competitive emerging technologies (e.g., wind power) are made early with and without carbon limits, to meet electricity demand. Without limits on carbon the remaining deployment of new capacity is made up of efficient, flexible, and low cost technologies (e.g., gas plants), whereas with limits on carbon, higher-cost carbon-free technologies with additional operational constraints such as nuclear power are deployed.

The deployment of a technology such as nuclear in the presence of a carbon limit occurs because its baseload nature affords deep emission cuts.

R&D investments track deployment patterns, preceding them based on current installed capacities and learning potentials as their benefits are realized when a technology is deployed and meeting electricity demand at a lower cost than the next marginal producer. R&D investments in early periods are optimal for technologies with high learning rates, but play an overall less dramatic role in meeting demand (e.g., both wind and solar are intermittent generating technologies). Following this, a greater share of R&D investment is allocated to wind than solar in the new model, because solar is represented as more resource constrained. Conversely, lower initial levels of R&D that increase gradually over time appear optimal for technologies with lower learning rates and deferred deployment (e.g., nuclear).

The modeling experiments in this paper demonstrate the impacts of embedding power sector details, such as operational constraints and interannual variability, and diminishing returns to energy R&D in state-of-the-art modeling frameworks for assessing joint R&D and capacity investment portfolios. The additional engineering cost and operations details of the electric power system provide a more precise look at the role that different technologies play to meet demand, and this, in turn, provides a better foundation to determine the optimal level of R&D that should be spent to support some emerging technologies over others.

Results show that when key characteristics of the electricity sector such as load variability, intermittent generation, and operational constraints such as cycling are excluded, the investment strategy can differ significantly from the reference solution. Specifically, under a carbon limit, the strategy from a simplified model can exclude investments in higher cost, intermittent renewables with high learning potentials (e.g., solar PV). In contrast, the reference model chooses an alternate investment path inclusive of these technologies, considering the niche roles for different intermittent renewable resources such as wind and solar PV. Our results also show that investment strategies for baseload technologies with significant engineering operating constraints and thermal inertias such as coal with CCS or nuclear power can be highly sensitive to the manner in which their operational constraints are imposed in the model, relative to other substitutable technologies. While this result seems obvious in hindsight, our numerical results support the notion that when integrating a model of power system operations and innovation to study joint R&D and capital investment decisions, it is not simply additional detail that matters. Preserving the relative contributions of different technologies to each other, and being consistent in representing their operational constraints while doing so, is important as well. Cost assumptions and engineering details included in the models impact the optimal investment strategy because they provide a more precise view of the usefulness and role of a technology relative to others in the actual system.

Sensitivity analyses and additional investigation into the effects of incorporating further power system details such as regional heterogeneity in existing capacity and renewable resource potential, support the broad conclusion that optimal joint R&D and capacity portfolios are sensitive to the level of representation of the power system and innovation processes in the model (see Section 3.5). When the new framework is applied to different regions, priorities for capacity and R&D investments shift. We conclude that R&D investments track the technology groups in the system that represent the long-run least cost option, but only once the opportunities for cost reduction through innovation are factored in. For example, in a system with a high existing nuclear resource base, additional R&D and capacity investments in nuclear are preferred early because costs are reduced dramatically in the near term, and over time. In a system with a more diversified existing portfolio, early investments are diversified until a clear winner is revealed to continue receiving R&D investment.

Finally, our results show that if diminishing returns to research effort are not explicitly represented in the model of innovation, the optimal strategy exhibits overinvestment in the near-term and underinvestment in later periods. This results from the fact that the average return rate from R&D investments appears to be much higher in a model without diminishing returns, thus reducing the benefit of continued investments. Additionally, the sensitivity of the optimal R&D investment strategy to the characteristics of the innovation process—elasticities of new knowledge to R&D and to knowledge stock— are similar to each other in that for the technologies with high learning rates and early period R&D investments, R&D investment tends to decrease (or stay constant) with increasing values for both innovation process characteristics. On the other hand, for technologies with low learning rates (e.g., nuclear) and deferred R&D investments, R&D investment tends to increase with higher values for these elasticities.

For future research, we have already identified above that a more systematic exploration of the change in direction and magnitude of the investment strategies with increasing power system detail would be beneficial to the energy modeling community. This effort was beyond the scope of the current paper. We have also noted the open opportunity to consider additional pathways of technical change in this type of a modeling framework. Beyond these topics, several additional directions for future research are worth considering.

First, it would be valuable to study the optimal R&D investment strategy under uncertainty in the return rate for R&D programs (R&D efficiency) and knowledge stock strength given the sensitivity of optimal R&D investments to the components of the knowledge building process, and the paucity of data available to estimate the value of these innovation process characteristics, One such study is Santen (2012), and Section 2 discusses other work in this area in the existing literature, but in general this is an open area of research that would benefit from multiple perspectives and new modeling frameworks.

Second, we have developed the current model using an engineering cost structure with the intention of presenting a framework that could be used as the “bottom-up” component of a more integrated hybrid modeling effort. There are many feedbacks between the electricity sector and the rest of the economy, as well as between the energy innovation that occurs in the electricity sector and the rest of the economy. The integration of a modeling framework such as the one presented here into a hybrid model that represents the feedbacks between sectors of the economy would be a valuable contribution.

Third, due to our focused research objective, we have used a model that relies on a single, aggregated entity that engages in innovative activity and chooses R&D investments only in response to opportunities for minimizing system-wide costs. However, in reality, innovation occurs via several different institutions, by both public and private entities that respond to different incentives. Representing public and private innovation separately in a model like the one we present here could help inform the allocation of R&D funds across different actors, as would characterizing and representing other key features of the innovation process such as R&D feedbacks upstream at the technology suppliers from downstream deployment at the utilities and power producers.

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