Online Supplement for Santen, N.R., Webster, M., Popp, D., and I.J. Perez-Arriaga (2016). "Inter-temporal R&D and capital investment portfolios for the electricity industry's low carbon future." *The Energy Journal 38*(5).

APPENDIX A. Summary: Structure and Features of Selected Energy Modeling Frameworks with Technical Change

Model/Study	**Top-Down Economic (e.g., Stylized Energy-Power Sector)**	**Bottom-Up Engineering Cost (e.g., Power Sector Technology Detail)**			**Uncertainty Focus (e.g., Stylized Innovation Process or Power Sector)**
		No R&D Decisions	*Stylized R&D (e.g., Linear)*	*Hybrid with R&D (e.g., Stylized Power Sector Operations)*	
Goulder & Schneider 1999	X				
Van der Zwaan, Gerlagh, Klaassen & Schrattenholzer 2002 (DEMETER)	X				
Buonanno, Carraro & Galeotti 2003 (ETC-RICE)	X				
Popp 2004 and Popp 2006 (ENTICE)	X				
Nordhaus 2010 (RICE)	X				
Ross 2008 (ADAGE)	X				
Pugh et al. 2011	X				
Short et al. 2011 (NREL ReEDS)		X			
Messner 1997 (MESSAGE)		X			
Mattheson & Wene 1997 (GENIE)		X			
Loulou, Goldstein & Noble 2004 (MARKAL)		X			
US Energy Information Administration 2009 (NEMS)		X			
Seebregts et al. 1999 (MARKAL)		X			
Kouvaritakis, Soria & Isoard 2000 (POLES)					
Barreto & Kypreos 2004 (ERIS)			X		
Manne, Mendelsohn & Richels 1995 (MERGE)				X	
Bosetti et al. 2006 (WITCH)				X	
Blanford 2009					X
Baker & Solak 2011					X
Ybema et al. 1998					X
Bosetti & Tavoni 2009				X	X
Kypreos, Barreto, Capros & Messner 2000		X			X
Messner, Golodnikov & Gritsevskii 1996					X
Grubler & Gritsevskii 2012					X
Webster, Fisher-Vanden, Popp & Santen (2015)	X				X

Notes: Section 2 of the paper includes definitions of each category.

APPENDIX B. Full Formulation of the Electricity Generation Capital and R&D Investment Planning Model

Indices and exogenous parameters

t	period
g	generation technology category
g^*	dispatchable technology categories
g^{**}	non-dispatchable technology categories
g^{***}	no new build technology categories
g^{****}	emerging (learning) technologies
d	demand slice
r	annual discount rate
$fix\_om\_rate_g$	fixed O&M cost for technology g
$duration_d$	length (in hours) for demand slice d
$fuel\_cost_{g,0}$	initial fuel cost for technology g
$fuel\_growth\_rate_g$	annual fuel cost growth rate for technology g
$var\_om\_rate_g$	variable O&M cost for technology g
$hebscale_g$	knowledge stock scaling parameter for technology g
$retire\_rate_g$	per period retirement rate for technology g
$CAPCOST_{g,0}$	initial capital cost for technology g
$\eta 1_g$	learning-by-doing elasticity for technology g
$\eta 2_g$	learning-by-searching elasticity for technology g
α_g, β_g, ϕ_g	innovation possibilities frontier parameters for technology g
δ_g	per period knowledge stock discount rate for technology g
$demand_d$	power level (gigawatts) for demand slice d
$emission\_rate_g$	carbon emission rate for technology g
$ecap$	cumulative carbon emissions cap
$availability\_rate_g$	availability rate (including maintenance & outages) for technology g
$demand\_peak$	power level (gigawatts) for peak demand slice
k	annual demand growth rate
$reserve\_margin$	reserve margin (%) for electricity reliability
$initial\_capacity_g$	initial installed capacity for technology g
$install\_uprate_{g^{****}}$	maximum installed capacity rate of change between periods for emerging technologies

Exogenous variables

RR_t	accumulated social discount factor in time t
KK_t	accumulated demand growth factor in time t
$FP_{g,t}$	accumulated fuel cost growth factor in time t for technology g

Endogenous variables

$RD_{g,t}$	R&D investment for technology g in period t
$NC_{g,t}$	new capital installations for technology g in period t
$IC_{,t}$	cumulative installed capacity for technology g in period t
FC_t	total fixed costs in period t
$VC_{g,t}$	variable costs for technology g in period t
$TOTAL\_CAPCOST_{g,t}$	capital investment costs for technology g in period t
$TOTAL\_FIX\_OM_{g,t}$	total fixed O&M costs for technology g in period t
$PWROUT_{d,g,t}$	total electricity generation for technology g in demand slice d in
E_t	total emissions in period t

$CAPCOST_{g,t}$	capital cost for technology g in time period t
$NEWK_{g,t}$	new human knowledge for technology g in period t
$KS_{g,t}$	human knowledge stock for technology g in period t
$NETLOAD_{d,t}$	net electricity demand (total demand less non-dispatchable generation technologies) in demand slice d in period t

Objective

$$\min_{NC_{g,t}, RD_{g,t}} NPV \qquad (1)$$

Objective Function Equations

$$RR_t = (1+r)^{-5(t-1)} \qquad (2)$$

$$[FC_{g,t} + VC_{g,t} + RD_{g,t}] * ¿\, RR_t$$
$$NPV = \sum_{g,t}^{G,T} ¿ \qquad (3)$$

$$OM$$
$$g,t$$
$$TOTAL_{¿}$$
$$TOTAL_{CAPCOST\,g,t} + \sum_{g}^{G} ¿ \qquad (4)$$
$$FC_t = \sum_{g}^{G} ¿$$

$$g,t$$
$$rate$$
$$g$$
$$fix_{¿}$$
$$TOTAL_{¿}\, 5\, IC_{g,t}\, ¿$$ (fixed costs per period) (5)

$$rate$$
$$g$$
$$\frac{fuel_{¿}}{100}$$
$$¿$$
$$1+(¿]$$
$$¿$$
$$¿$$
$$FP_{g,t}=¿$$

(6)

$$rate$$
$$g$$
$$var_{¿}$$
$$fu\,el_{costg,0}FP_{g,t}+¿$$
$$PWROUT_{d,g,t}duration_{d}¿$$
$$VC_{g,t}=5\sum_{d}^{D}¿$$

(variable costs per period) (7)

$$TOTAL_{CAPCOST\,g,t}=CAPCOST_{g,t}NC_{g,t}hebscale_{g,t} \tag{8}$$

$$NC_{g,t}=IC_{g,t}-\left[IC_{g,t-1}\left(1-retire_{rateg}\right)\right] \tag{9}$$

$$CAPCOST_{g,t}=\frac{CAPCOST_{g,0}}{\left(IC_{g,t}^{\eta 1_g}\right)\left(KS_{g,t}^{\eta 2_g}\right)}$$

(2-factor learning curve) (10)

$$NEWK_{g,t}=\alpha_g\frac{1}{5}RD_{g,t}^{\beta}KS_{g,t}^{\phi}$$

(annual innovation possibilities frontier) (11)

$$KS_{g,t+1}=5\,NEWK_{g,t}+\left(1-\delta_g\right)KS_{g,t}$$

(knowledge stock accumulation) (12)

$$E_t=5\sum_{d,g}^{D,G}emission_{rate\,g}PWROUT_{d,g,t}duration_d$$

(emissions per period) (13)

Constraints

$$\sum_{t}^{T} E_t \leq ecap$$ (cumulative emissions cap) (14)

$$\sum_{g^{¿}}^{G^{¿}} PWROUT_{d,g^{¿},t} = NETLOAD_{d,t}$$ (electricity demand balance) (15)

$$KK_t = (1+k)^{5(t-1)}$$ (16)

$$NETLOAD_{d,t} = demand_d KK_t - PWROUT_{¿}^{d,g^{¿*¿,t}}$$ (17)

$$PWROUT_{d,g,t} \leq IC_{g,t}$$ (18)

$$\sum_{d}^{D} PWROUT_{d,g,t} duration_d \leq IC_{g,t} ¿ 8760 * availability_{rateg}$$ (19)

$$\sum_{d}^{D} PWROUT_{d,g*¿,t} = IC_{g*¿,t}\, availability_{rateg*¿}$$ (20)

$$\sum_{g}^{G} IC_{g,t} \geq demand_{peak} \times KK_t (1 + reserve_{margin})$$

(reliability requirement) (21)

$$IC_{g,1} = initial_{capacity\,g}$$ (starting with the existing system) (22)

$$IC_{g*¿*¿,t+1} \leq install_{uprateg*¿*¿} \times IC_{g*¿*¿,t}$$

(maximum rate of change for installed capacities) (23)

$$NC_{g*¿*,t} = ¿ \quad 0 \qquad \text{(no new builds for outdated technologies) (24)}$$

APPENDIX C. Model Inputs and Assumptions

Table C1. Electricity Generator Data

Technology	**Initial Capacity** [GW]	**5-year Retirement Rate** [%]	**Heat Rate** [MMbtu/MWh]	**Initial Capital Cost** [$/kW-knowledgeunit]	**Fixed O&M Cost** [$/kW-year]	**Initial Fuel Cost** [$/MMBtu]	**Other Variable Cost** [$/MWh]	**Emissions Rate** [lbs/MMbtu]	**Annual Availability Rate** [%]
Old Coal	300	15	10.00	1204	23.410	2.28	4.14	205	85
New Coal	1	-	8.80	3167	35.970	2.28	4.25	205	85
Coal with CCS	1	-	12.00	5099	76.620	2.28	9.05	20.5	80
Old Steam Gas	100	20	9.46	390	25.256	5.16	3.85	137	80
Gas Combined Cycle	200	-	6.43	1003	14.620	5.16	3.11	119	90
Gas Combustion Turbine	100	-	9.75	665	6.700	5.16	9.87	119	90
Hydro	100	-	10.34	1320	12.700	-	3.20	-	90
Nuclear	100	10	10.40	5355	85.663	0.62	0.48	-	90
Wind	50	-	-	2438	28.070	-	-	-	30
Solar	1	-	-	4755	16.700	-	-	-	95[1]

Notes:
[1] The availability rate for solar is high due to the technology only operating during peak solar demand slices.
References: Short et al., 2011; EIA, 2010a; EIA, 2010b

Table C2. Growth Rates and System-Wide Parameters

Parameter	Value
Cumulative Emissions Cap No Policy/Policy, *ecap*	140,000/60,000 Million Metric Tons
Electricity Supply Reliability Reserve Margin, *m*[1]	10%
Annual Electricity Demand Growth Rate, *k*	0.5%
Annual Discount Rate, *r*	5%
Coal Price Annual Growth Rate, $fuel\_growth_c$	4%
Gas Price Annual Growth Rate, $fuel\_growth_{ng}$	1%
Maximum Rate of Change for Emerging Technology Installed Capacities Per Period, $install\_uprate_g$	2.0

Notes:
[1] The reserve margin is applied in the model as a generation requirement above "net load."

Table C3. Reference Model Technical Change Parameters

Technology	Learning-by-Doing Elasticity η1	Learning-by-Searching Elasticity η2	IPF a	IPF	IPF β
Coal with CCS [1]	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
*Note, this table is listed as Table 1 in the full paper.

1 The lack of 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. Thus, 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 (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 of space, scale up, public acceptance, permitting, waste, etc.).

Table C4. ERCOT-like and Mid-Atlantic-like System Electricity Resource Bases

Technology	**Initial Capacity** [GW]	**Initial Capacity** [%]	**Initial Capacity** [GW]	**Initial Capacity** [%]	**Reference Model Initial Capacity [%]**
	ERCOT-like	***ERCOT-like***	***PJM-like***	***PJM-like***	***US***
Old Coal	20	25%	80	45%	31%
New Coal	1	1%	1	1%	1%
Coal with CCS	1	1%	1	1%	1%
Old Steam Gas	10	13%	15	8%	10%
Gas Combined Cycle	30	38%	30	17%	21%
Gas Combustion Turbine	10	13%	10	6%	10%
Hydro	1	1%	10	6%	10%
Nuclear	5	6%	30	17%	10%
Wind	1	1%	1	1%	5%
Solar	1	1%	1	1%	1%
TOTAL	80		179		

Notes:
Defining features of each region are indicated by shaded cells. The minimum capacity for any technology in the numerical model is 1 (GW).
Sources: ERCOT 2014; PJM 2014 (values above are approximates based on these sources)

TableC5. ERCOT-like and PJM-like System Demand and Region-Specific Solar and Wind Capacity Factors by Time Slice

Time Slice	Duration [hrs]	Demand [GW]	Demand [GW]	Wind CF [%]	Wind CF [%]	Solar CF [%]	Solar CF [%]
		ERCOT-like	***PJM-like***	***ERCOT-like***	***PJM-like***	***ERCOT-like***	***PJM-like***
1	736	40.93	84.22	0.284	0.105	-	-
2	644	37.78	96.25	0.483	0.103	0.221	0.316
3	328	51.78	122.03	0.255	0.070	0.571	0.504
4	460	55.80	116.12	0.160	0.085	0.298	0.146
5	488	31.72	72.48	0.252	0.215	-	-
6	427	31.41	84.29	0.450	0.203	0.179	0.241
7	244	38.96	88.60	0.292	0.170	0.558	0.438
8	305	35.74	90.85	0.296	0.170	0.248	0.052
9	960	30.56	84.77	0.275	0.312	-	-
10	840	32.48	92.98	0.358	0.297	0.110	0.159
11	480	34.55	92.61	0.304	0.297	0.470	0.392
12	600	35.20	98.77	0.268	0.257	0.144	0.035
13	736	31.20	70.63	0.397	0.237	-	-
14	644	30.53	82.93	0.580	0.241	0.184	0.290
15	368	38.15	87.81	0.435	0.192	0.569	0.501
16	460	40.61	88.10	0.346	0.187	0.273	0.114
17	40	62.60	92.16	0.204	0.091	0.578	0.487

Notes: The region with the higher level of renewable resource in each category is shaded. Demand of the PJM-like system is almost twice as large as the ERCOT-like system. The TX system is windier than the Mid-Atlantic. Solar resources are more comparable, with TX having slightly stronger resources during more slices.
Sources: ERCOT 2012; PJM 2012; EPA 2014

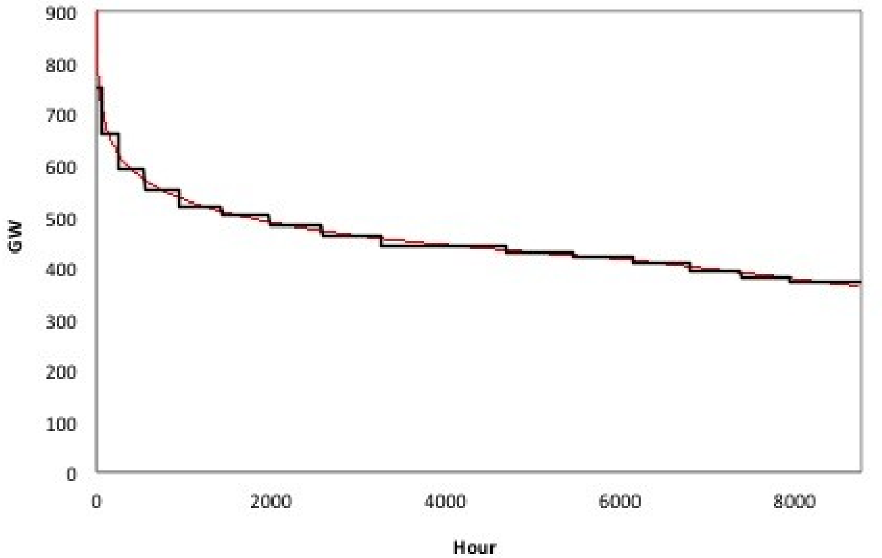


Figure C1. Load Duration Curve Used (Original Source: Short et al. 2009)

APPENDIX D. Detailed Operations Model Analyses

In addition to developing a simplified model, we also constructed a highly-detailed engineering operations model (hereafter referred to as the "detailed operations model") on a test-system, against which we compared results to a replica of the reference model on the same test-system[2]. The objective of this variation was to determine whether *increasing* levels of engineering detail resulted in amplified (and unidirectional) changes of those seen when moving from the simplified power systems model to the reference model. While the scope of the existing work was to develop a framework for integrating *better* technical change dynamics and *better* power system details to tackle the joint R&D and capacity planning problem, as described in Section 2, state-of-the-art power systems models do contain a much more sophisticated representation of engineering reality than the reference model. Thus, the goal was to see whether results from the reference model were maintained when pushing engineering reality even further. Conversely, if they changed in a meaningful way, what insights can those changes provide?

The detailed operations model featured hourly demand and chronological generator dispatch; individual generating unit commitments; technology-specific start-up and shut-down costs, ramp rates, and minimum-maximum outputs; and hourly profiles of wind and solar capacity factors for an actual region. Four representative weeks (one in each season) were modeled hour-by-hour, and annual generation for a base year was compared to generation for the base year from the reference model. To keep computational time for this this test reasonable, we removed the technical change dynamics from this test. We exploit our earlier finding that R&D investments track the role a technology can play in meeting demand; the technical change dynamics would be the same between both models, so seeing how individual technologies operate (generate electricity) differently between the two models is sufficient to understand how their opportunities from R&D would change.

Figure E1 compares MWh electricity production by technology group in the reference model and the detailed operations model. Generation for solar PV and wind are reasonably consistent between the two models, nuclear displayed higher generation while coal displayed slightly lower generation in the operations model, and coal with CCS and gas are relied on more in the operations model. Minor differences in generation and the overall general preference of gas units are not unexpected in the detailed operations model. Given fast ramp rates of gas units, there is an opportunity to cost-effectively cycle them to meet demand; the additional engineering detail in this type of a model better represents gas units' competitive position. Conversely, a model with less temporal resolution like the reference model is unable to represent realistic decisions on shorter time-scales, and can thus blur operations.

The increased use of coal with CCS units in the detailed operations model is an important result. Moving from simple to most detailed frameworks—simplified power systems model, reference model, and finally detailed operations model—electricity produced from coal with CCS is relatively high, then low, then high again, respectively. Although this may appear initially surprising, this behavior is a result of how the operating position of coal with CCS is represented alongside other substitutable technologies (e.g., nuclear) in the different versions of the model, as well as how the quantity of available generating capacity is represented in the different models.

First, in the detailed operations model, the increased use of coal with CCS is reflective of the technology's minimum output and slow downtime constraint. Once these units are on, they must meet load for a minimum amount of time. Nuclear power in the detailed operations model also has a minimum output and two-fold higher downtime constraints, and is even more constrained with relatively high start-up and shut-down costs. In the reference model, these constraints do not exist for coal with CCS. Only the nuclear technology is instead represented as a "baseload" must run technology, and its generation thus effectively displaces generation that would otherwise occur from coal with CCS. In the simplified power systems model, the opposite result is encountered once again, but for a different reason. In the simplified model, coal with CCS remains free of operating constraints, but so does nuclear, creating an artificially-level playing field.

---

2 The modeled test system (including resource base, and renewable resource profiles) was roughly equivalent to 1/10th of the ERCOT (TX) system modeled. A business-as-usual carbon scenario was modeled.

Second, in the detailed operations model, generators are represented as discrete power plants with a set quantity of production capacity, whereas in the reference model and in the simplified model generators are represented as a continuum of capacity (e.g., a single megawatt of nuclear capacity can be built and called upon to generate power). This means that in the detailed operations model, it is more difficult for nuclear power to substitute for coal with CCS, if the coal with CCS plant is already committed and operating. In this case, the system will first use power from all producing MW of that designated coal with CCS plant before selecting another resource. Combined, the operating constraints described above and representation of discrete plants versus continuous MW of generation supply result in a non-monotonic response of coal with CCS generation when moving from the simplified model to the reference model to the detailed operations model.

Overall, this test shows that common methods for designating technologies as "baseload" versus otherwise available need to be carefully considered in the context of defining relative positions of substitutable technologies. The reference model seems to be accurately capturing relative investments paths for wind and solar, and the investment strategy for low-carbon baseload technologies will follow their relative usefulness in the generating portfolio. Thus, keeping the relative positions of technologies may likely be the more important driver in understanding cost-effective R&D investment opportunities than simply adding engineering reality. This investigation is beyond the scope of the current paper which aims to outline a structure for bringing additional innovation details together with power system details, but would be a valuable line for future research.

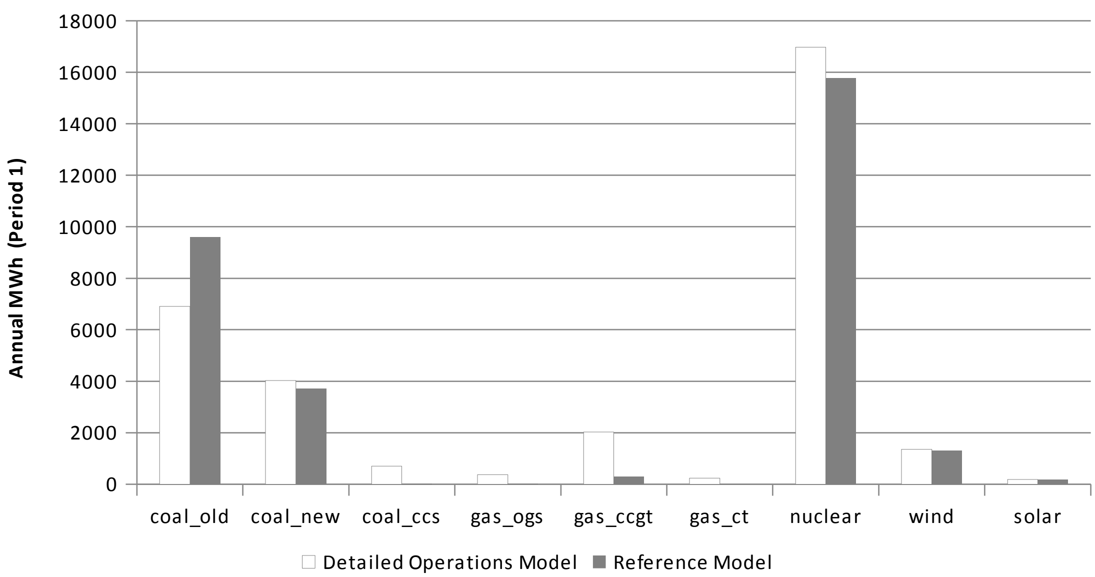


Figure E1. Electricity production by technology in reference model and detailed operations model.

APPENDIX E. Sensitivity Analyses

Sensitivity Analysis #1: optimal investment strategies v. knowledge building components

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 (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 technical change literature showing variation across energy technologies in the contribution of their knowledge stocks to successful innovation (Popp et al., 2013). In the reference model (Section 3.1), we assume values of β and φ from the literature, assigning all emerging technologies the same values.[3] Here we summarize results from sensitivity analyses of the optimal strategy to both of these elasticity parameters. We focus on the impact on R&D investments.

Figure F1 shows the share of peak R&D investments over time, in each of the four emerging technology groups for a range of R&D investment efficiency (parameter β) values under a carbon limit (reference value for β is 0.1). With increasing R&D efficiency, the shares of wind and solar power (technologies with high learning rates and early R&D) investments display only mild sensitivity; the R&D investment shares for these technologies decrease slightly as R&D efficiency increases. In contrast, nuclear power, which has a much lower learning rate and an optimal path of R&D that peaks in later periods, sees increasing investment shares with increasing R&D efficiency. The general trend is robust to R&D investment efficiencies. It is optimal to invest the largest share into nuclear, the next largest share into wind, the least into solar, and none into coal with CCS.

The optimal investment pattern is more sensitive to assumptions about φ, the elasticity of new knowledge production to current knowledge stock levels (Figure F2). As this elasticity increases, the relative share of wind R&D investments decrease and the relative share of nuclear R&D investments increase. Specifically, for values of φ below approximately 0.4 (reference value is 0.54), it is optimal to invest the majority of R&D into wind over nuclear, but for values greater than 0.4, it is optimal to invest the majority of R&D into nuclear power. The effect on optimal R&D share for solar and coal with CCS is more robust to the knowledge stock elasticity. It is optimal to spend approximately one-tenth of total R&D expenditures on solar PV technology for any value of knowledge stock strength. The optimal strategy continues to exclude R&D or capital investments into coal with CCS across all values of β and φ studied here, for this version of the model.

We conclude that for technologies for which early R&D investments are optimal and learning rates are high (e.g., wind), more efficient innovation processes lead to a lower share of R&D investment into those technologies. The intuition is that if the same amount of R&D expenditures yields greater returns, there is no need to spend extra money. Additionally, because expenditures take place in the first few years for these technologies, there is less time to benefit from accumulating knowledge. However, for technologies with low learning rates and deferred R&D investments (e.g., nuclear), increasing the elasticity of new knowledge to the knowledge stock leads to an increased share of R&D investment. In these cases, there is more time for benefits from additional R&D to accrue. Discounting of future period R&D investments also makes an increase in R&D in later years a less costly decision.

3 Although parameters β and φ of the innovation possibilities frontier are the same across the four emerging technologies, a scaling parameter α is used to calibrate each technology to *technology specific* learning values in the literature allowing each technology to follow its own cost-reductions over R&D investment (See Section 3 for more details).

When compared side-by-side, the sensitivity of the optimal investment strategy in terms of relative shares of R&D investment to both R&D aknowledge 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, as Figure F2 below shows, 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. For low values for this parameter, the model results indicate that it is optimal to invest the majority of the R&D expenditures on wind, whereas for high values for this parameter nuclear R&D becomes the priority. Given the limited empirical data on these parameters, and the inherent uncertain nature of the innovation process, we leave the exploration of the impact of uncertainty in these parameters as future work.

Sensitivity Analysis #2: optimal investment strategy and regional electricity system heterogeneity

In a second sensitivity analysis, we studied the effect of geographic variation on the optimal investment strategy. Embedding detailed regional characteristics of the physical electric power system and its operations is outside the scope of this paper, which aims to open a discussion about the impact of greater model resolution when analyzing joint R&D and capacity decisions. However, regional differences in the underlying generation capacity portfolio and renewable resource potential—among many other factors—play an important role in defining opportunities for new technologies. 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. Below, we discuss how the results change across regions and comment on the impact that regional heterogeneity has on the aggregated results and insights from the reference model.

We constructed two alternative versions of the reference model, but instead applied demand profiles, underlying electricity generation resource portfolios, and region-specific hourly profiles for wind and solar capacity factors (mapped on to the original 17 time slices) that are representative of the Electric Reliability Council of Texas (ERCOT) and Pennsylvania-New Jersey-Maryland Interconnection (PJM) Mid-Atlantic electricity systems. Tables 5 and 6 show the heterogeneity between these regions, and compares them to the aggregate U.S.-level implementation of the reference model. Overall, fossil (gas, and to a lesser extent coal) dominate the TX portfolio; while fossil, nuclear, and some hydro dominate the Mid-Atlantic portfolio. With respect to renewable resources, the TX system has abundant wind and solar resources, but the Mid-Atlantic has a comparably stronger solar resource (as measured by historical hourly capacity factors). In comparison, the US-level reference model includes a more diverse generating portfolio, with a mix of coal, nuclear, gas, and hydro, and uses a single resource availability factor for wind and solar. Figures F3 and F4 show the R&D and capacity investment strategy paths for each of these regions. For comparison, the U.S.-level reference model investment strategies are in Figures 1 and 2 in the paper.

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. As in the reference model, learning-based cost reductions occur more rapidly for nuclear than for coal with CCS due to nuclear power's greater existing capacity (LBD), and subsequent larger knowledge stock base (LBS). As expected, the timing for these capacity investments and for the corresponding R&D, is tied to the relative shares of existing capacity in a specific region. For example, higher levels of nuclear R&D investment are delayed in PJM compared to ERCOT because of the underlying high initial ratio of base load coal in PJM and resulting lack of need for additional base load capacity. After coal units are retired, nuclear dominates both the capacity and the R&D investments.

The patterns for wind and solar capacity and R&D follow the relative abundance of these energy resources in each region. ERCOT has both high solar and high wind resources, and under a carbon cap both resources continue to be invested in for new capacity and R&D. PJM, in contrast, has relatively lower quality wind but moderate solar resources, and this results in solar accounting for a large share of the capacity and R&D investments when there is a carbon cap. The reliance on a region's highest quality renewable energy resource, and preferential R&D investment in it, is seen more clearly in the business-as-usual cases. ERCOT exploits exclusively wind, while PJM exploits solar, both continuing to drive the capital costs of those technologies down as far as possible through R&D. A more balanced approach is taken in the national-level model, because the average resource availability across the country is roughly comparable between wind and solar, even though in individual regions one may dominate the other.

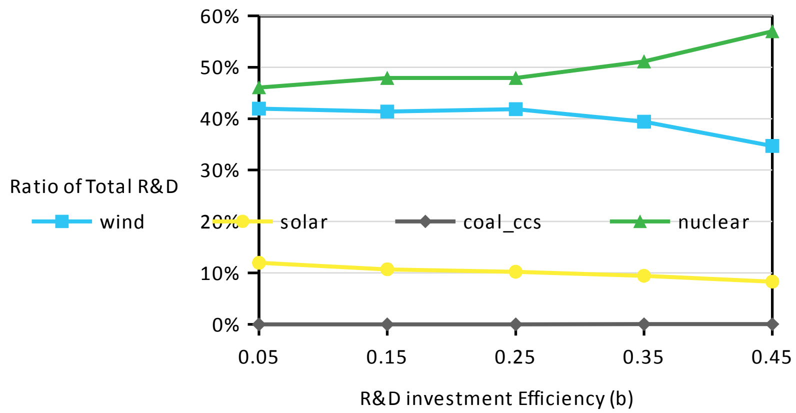


Figure F1. Peak optimal R&D investments for various R&D efficiencies (value for β in the Innovation Possibilities Frontier) under a carbon limit.

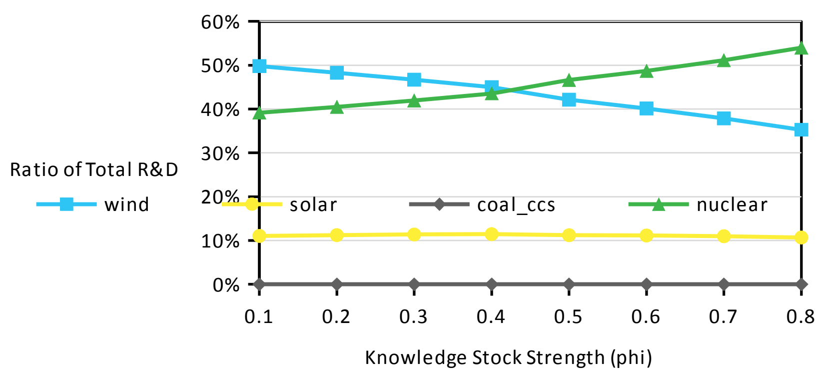
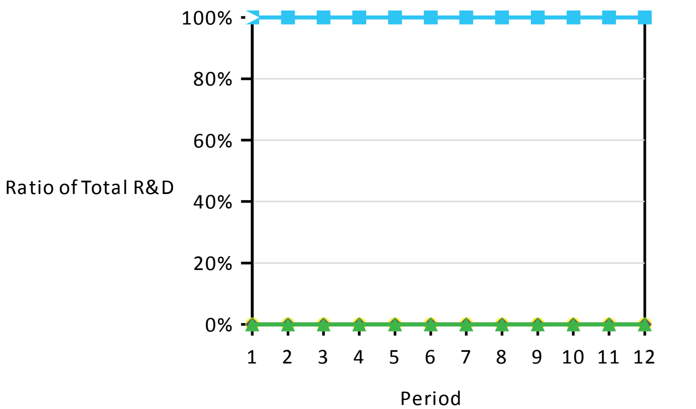
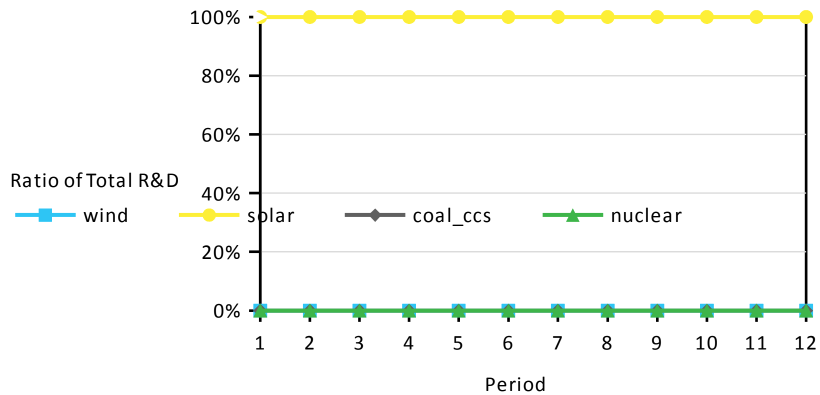


Figure F2. Peak optimal R&D investments for various knowledge stock strengths (φ values in the "Innovation Possibilities Frontier") under a carbon limit.

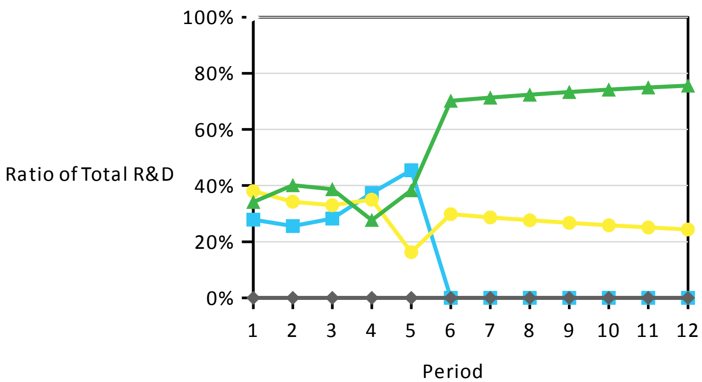
(a) ERCOT-like R&D <u>with no</u> carbon limit



(b) PJM-like R&D <u>with no</u> carbon limit



(a) ERCOT-like R&D <u>with</u> carbon limit



(d) PJM-like R&D <u>with</u> carbon limit

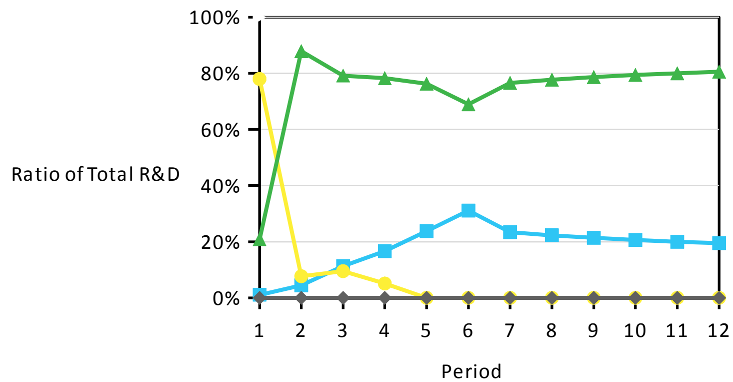


Figure F3. Regional results. Ratios of optimal R&D investments to total R&D investments per period. Compare to paper Figure 1 for U.S-level results

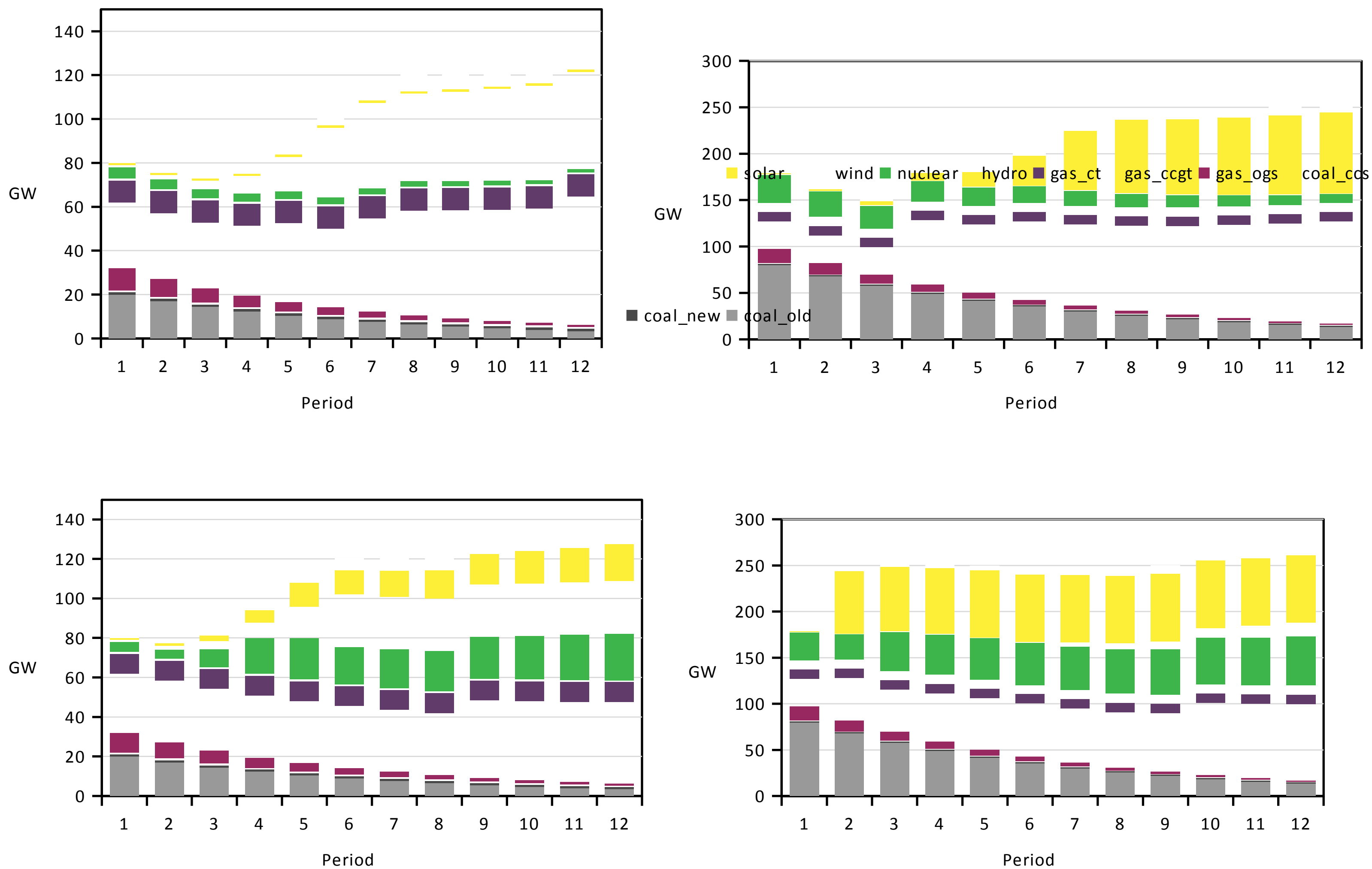


Figure F4. *Left:* ERCOT-like region optimal installed generation capacity under no carbon limit (top) and a carbon limit (bottom). *Right:* PJM-like region optimal installed generation capacity under no carbon limit (top) and a carbon limit (bottom). Compare to paper Figure 2 for U.S-level results.