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How Climate-Related Policy Affects the Economics of Electricity Generation

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Abstract
Purpose of Review Concerns surrounding climate change are increasing pressure on policymakers to reduce greenhouse-gas emissions. A number of policy mechanisms, including Pigouvian taxes on carbon and subsidies for and mandates on the use of carbon-free generation, are among the levers that are used to achieve this goal. A challenge that such mechanisms present is that they can distort energy markets, affecting prices and the financial viability of investing in or maintaining generating capacity.
Recent Findings We survey literature pertaining to how policy mechanisms impact markets and short- and long-run economic signals. We present also a case study that examines these issues. Our case study uses a two-step modeling procedure. First, a long-term generation- and transmission-planning model determines the optimal technology mix that should be built to serve future loads under different climate-policy regimes. Next, a unit-commitment model is used to simulate hourly operation of the system. Combining the results of these two modeling steps, we assess the efficiency of using different policy mechanisms to achieve carbon reductions.
Summary Based on our literature survey and case study, we find that market-based policies (*e.g.*, carbon taxes) achieve decarbonization targets most efficiently. Moreover, market-based policies are the least distortionary in terms of price formation in wholesale electricity markets.

Keywords Energy policy · climate policy · energy markets · generation investment · cost recovery · energy economics

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1 Introduction

Traditional electricity markets consist typically of vertically integrated utilities that recover their costs through cost-of-service regulation. Typically, cost-of-service regulation entails a regulatory body setting retail utility prices based on an estimate of the cost of serving customers and an added rate of return [1, 2]. The added rate of return is intended to reflect the utility's cost of capital. Normally, this form of regulation does not provide strong incentives for cost containment and cost risks often are shifted to customers. As such, beginning in the 1980s, a number of jurisdictions have introduced electricity-market reforms. The aim of these reforms is to place more cost risk on investors, which can yield more prudent investment decisions.

Two mechanisms are employed commonly in restructured wholesale electricity markets to provide generators with opportunities to recover their costs. The first, which is referred to often as an energy-only market design, relies solely on scarcity pricing of energy and operating reserves. Stoft [3] provides a stylized model that outlines how cost-recovery using energy prices only works. Stoft shows also that if the generation mix of an electricity system is optimal (in the sense of being welfare-maximizing), the marginal energy prices that emerge from a perfectly competitive market are guaranteed to recover all generator costs. The other cost-recovery mechanism employs a capacity payment, which supplements energy and reserve payments. There are a number of reasons that capacity markets may be employed to handle cost recovery [4, 5]. For one, scarcity pricing in an energy-only market may be harmed by market mitigation, which are steps that are taken to reduce the exercise of market power by generators. Capacity markets also can accommodate complexities such as lumpy investments, economies of scale, and other market features that do not fit the stylized model that underlies the energy-only market design.

Cost recovery in a restructured electricity market can be complicated further in the presence of policy interventions. Policymakers, legislators, and regulators are addressing climate-change concerns through a mix of policy interventions. Among these mechanisms are Pigouvian taxes on carbon emissions, direct subsidies (*e.g.*, production- or investment-tax credits or feed-in tariffs) for carbon-free generation, and mandates on the usage of carbon-free generation (*e.g.*, renewable portfolio standards). These types of policy interventions impact cost recovery because they distort investment decisions. The stylized energy-only model that Stoft [3] analyzes assumes that generation investments are made based purely on the economics of supplying demand. A renewable portfolio standard (RPS), as an example, results in some investments being made for policy as opposed to economic reasons.

This paper contributes to understanding the interplay between electricity markets and climate policy in two ways. First, we survey formative works that examine this topic. This includes modeling exercises that examine the impacts of high penetrations of renewable energy resources on price formation, the functioning of electricity markets, and cost recovery. Second, we present results from an illustrative case study that compares the market-efficiency and -distortion properties of three climate-change-mitigation policies: carbon taxes, an RPS, and a production tax credit (PTC) for renewable energy. Our case study demonstrates that carbon taxes are the most and RPS the least efficient means of achieving a desired level of carbon reductions. We find also that carbon taxes are the least distortionary on investment incentives whereas a PTC and RPS can exacerbate revenue-deficiency problems for generators.

The remainder of this paper is organized as follows. First, we provide a literature survey. Next, we detail the model and data that underlie our case study. This is followed by case-study results and conclusions.

2 Literature Survey

Concerns surrounding climate change are leading to increased use of policies to decarbonize the electricity sector. However, with few exceptions (European Union Emissions Trading System[1] being one), most jurisdictions are not addressing carbon emissions directly through taxes [6] or cap-and-trade schemes [7]. Rather, most policies address climate change indirectly by providing subsidies to or setting targets for the deployment and use of carbon-free technology, such as renewable energy [8]. A number of works compare the relative merits of policy mechanisms to incentivize the use of renewable energy, with Lipp [9] providing a comprehensive and seminal discussion. Given this approach to climate-change policy, we focus our literature survey on the impacts of high renewable-energy penetrations on the functioning of wholesale electricity markets and price formation and cost recovery therein.

Ela *et al*. [10] discuss the evolution of wholesale electricity markets with increasing renewable-energy penetrations. They do not provide specific market-design recommendations. Rather, Ela *et al*. conduct an agnostic survey of market evolution and identify two key market-design challenges that arise from renewable integration. One is providing price signals to incentivize flexibility for short-term operations. The second is ensuring sufficient revenues for capacity to be built and maintained for long-term reliability. Milligan *et al*. [11] explore wholesale electricity market designs to incentivize investments in resources that are necessary for system reliability with high renewable-energy penetrations. Their work recognizes the investment and capacity-expansion challenges that are created by variable availability of renewable energy in real time. They examine also the need for greater supply-side flexibility to ensure that demands can be served reliably with renewable variability and uncertainty. Mormann *et al*. [12] provide an empirical survey that compares market and policy designs in California, Texas, and Germany. By comparing outcomes in the three regions, they draw conclusions regarding how policy and market-design choices can impact the technical and economic efficiency of integrating renewables into electricity systems.

These types of analyses [10–12] give rise to works that provide more prognostic analyses of wholesale-market designs. Riesz *et al*. [13] model the performance of Australia's National Electricity Market, assuming that it maintains its current energy-only design with 100% penetration of renewables. They find that the energy-only design may work without the need for an explicit capacity market, but that this result depends on some critical assumptions. Importantly, the price cap in the market would need to be raised substantially (they estimate from a price of 13500 AUD/MWh at the time of their work to 60000 AUD/MWh–80000 AUD/MWh in the future

[1] https://ec.europa.eu/clima/policies/ets_en

that they model). Alternatively, demand-side participation, which allows customers to specify their willingnesses to pay for various levels of supply reliability [14], could obviate the need for high price caps. Regardless of the approach that is taken, the market likely needs a liquid derivatives market to allow hedging of significant price risk and volatility. Jenkin *et al*. [15] investigate capacity-market designs in the presence of high renewable-energy penetrations. Their work is cautionary—if markets are not designed properly, high renewable-energy penetrations may yield greater price volatility and revenue deficiency for capacity resources. This can lead to further suboptimal market-design choices. They suggest that important challenges remain in designing markets that provide adequate incentives for investing in capacity and operational flexibility (which are the key challenges that Ela *et al*. [10] raise). Levin and Botterud [16] analyze the impacts of increasing wind penetrations on electricity and reserve prices by solving a mixed-integer optimization that co-optimizes capacity-expansion, unit-commitment, and dispatch decisions. They find that revenue-deficiency problems (absent scarcity pricing, no thermal units are profitable) can be addressed through scarcity pricing or capacity payments. However, the required capacity payments are increasing in the wind-penetration level. Morales *et al*. [17] propose a revision to pool- and balancing-energy pricing that is tailored to a wholesale market with high penetrations of wind generation. They demonstrate that their proposed prices allow for generator-cost recovery and that the market is revenue-adequate (*i.e*., payments from loads cover payments to generators).

One gap in extant modeling exercises that examine the financial viability of generation [11, 13, 15, 16] is that they assume an exogenously set renewable-penetration level. The case study that we present addresses this gap by examining market economics that result from the use of different policy levers. While these policy levers affect renewable-penetration levels, they impact the generation mix in other ways as well. Thus, our work provides a comprehensive assessment of how policy decisions impact the market, as opposed to focusing solely on renewable energy.

3 Case-Study Methodology

Our case study entails two modeling steps. First, we model the least-cost mix of generation and transmission capacity to serve future demand. Next, we fix the generation and transmission mix (based on the first step) and use a unit-commitment model to determine the hourly operation of the power system. Both models are formulated to capture endogenously the effect of policy mechanisms.

3.1 Generation- and Transmission-Expansion Model

We adapt the model of Liu *et al*. [18, 19], to which readers are referred for further details, to represent generation- and transmission-expansion decisions. We provide a model formulation, but exclude many of the implementation details for sake of brevity. The planning model consists of investment epochs, each one spanning multiple years. Investment decisions are made at the beginning of each epoch. Power-system operations between the epochs are captured by modeling representative days.

3.1.1 Model Notation

Sets and Set-Related Parameters

N	set of generation technologies.
N^{ρ}	set of generation technologies to which the RPS applies.
R	set of transmission zones.
T^D	set of operating days between investment epochs.
T^H	number of operating hours during each representative day.
T^I	set of investment epochs.
Υ^I	number of years between investment epochs.
Ω	set of scenarios.
$\bar{\omega}_i$	set of scenarios that are indistinguishable from scenario ω when making investment decisions during investment-epoch i.

Parameters

A_n	lifetime of technology n (investment epochs).
$\bar{B}_{n,r,i}$	maximum capacity of technology n that can be built in zone r during investment-epoch i (MW).
$C^E_{\omega,n,r,i}$	cost of retiring technology n in zone r during investment-epoch i of scenario ω ($/MW).
$C^G_{\omega,n,r,i}$	generation cost of technology n in zone r during investment-epoch i of scenario ω ($/MWh).
$C^{G,\sigma}_{\omega,n,r,i}$	PTC for technology n in zone r during investment-epoch i of scenario ω ($/MWh).
$C^{G,\tau}_{\omega,n,r,i}$	carbon tax for technology n in zone r during investment-epoch i of scenario ω ($/MWh).
$C^L_{\omega,r,r'}$	investment cost of building transmission between zones r and r' during investment-epoch i of scenario ω ($/MW).
$C^M_{\omega,n,r,i,a}$	maintenance cost of technology n in zone r during investment-epoch i of scenario ω that is a epochs old at the end of the epoch ($/MW).
$C^S_{\omega,r,i}$	investment cost of energy storage in zone r during investment-epoch i of scenario ω ($/MW).
C^U	cost of unserved load ($/MWh).
$C^V_{\omega,n,r,i}$	investment cost of building technology n in zone r during investment-epoch i of scenario ω ($/MW).
$L_{\omega,r,i,d,h}$	zone r's load during hour h of day d of investment-epoch i of scenario ω (MW).
γ	discount rate.
δ_n	ramping factor of technology n (p.u.).
η	energy capacity of energy storage (h).
ζ	roundtrip efficiency of energy storage (p.u.).
π_ω	probability of scenario ω.
ρ_i	investment-epoch-i RPS (MW).
$\phi_{\omega,n,r,i,d,h}$	capacity factor of technology n in zone r during hour h of day d of investment-epoch i of scenario ω (p.u.).
$\Upsilon_{i,d}$	weight on representative day d of investment-epoch i (days).

Decision Variables

$k^E_{\omega,n,r,i,a}$ capacity of technology n in zone r with age a that is retired economically during investment-epoch i of scenario ω (MW).

$k^G_{\omega,n,r,i,a}$ total capacity of technology n that is installed in zone r with age a at the end of investment-epoch i of scenario ω (MW).

$k^L_{\omega,r,r',i}$ capacity that is added to transmission link between zones r and r' during investment-epoch i of scenario ω (MW).

$k^S_{\omega,r,i}$ capacity of energy storage that is installed in zone r during investment-epoch i of scenario ω (MW).

$K_{\omega,i}$ vector denoting all scenario-ω investment variables (*i.e.*, k's) of investment-epoch i.

$q^C_{\omega,r,i,d,h}$ hour-h power charged during day d of investment-epoch i of scenario ω into energy storage that is in zone r (MW).

$q^D_{\omega,r,i,d,h}$ hour-h power discharged during day d of investment-epoch i of scenario ω from energy storage that is in zone r (MW).

$q^G_{\omega,n,r,i,d,h}$ hour-h production during day d of investment-epoch i of scenario ω from technology n in zone r (MW).

$q^L_{\omega,r,r',i,d,h}$ net power flow during hour h of day d of investment-epoch i of scenario ω on link from zone r to r' (MW).

$q^S_{\omega,r,i,d,h}$ hour-h ending state of energy (SOE) during day d of investment-epoch i of scenario ω of energy storage that is in zone r (MW).

$q^U_{\omega,r,i,d,h}$ hour-h unserved load in zone r during day d of investment-epoch i of scenario ω (MW).

3.2 Model Formulation

The generation- and transmission-expansion model is formulated as:

$$\begin{aligned}
\min \sum_{\omega\in\Omega} \pi_\omega \sum_{i\in T^I} \gamma^{i\Upsilon_I} \cdot \Bigg\{ \sum_{n\in N, r\in R} \Big[C^V_{\omega,n,r,i} k^G_{\omega,n,r,i,1} \qquad (1)\\
+ C^E_{\omega,n,r,i} \cdot \left(k^G_{\omega,n,r,i,A_n} + \sum_{a=1}^{A_n-1} k^E_{\omega,n,r,i,a} \right) + \sum_{a=1}^{A_n} C^M_{\omega,n,r,i,a} k^G_{\omega,n,r,i,a} + \sum_{r\in R} C^S_{\omega,r,i} k^S_{\omega,r,i} \\
+ \sum_{d\in T^D} \Upsilon_{i,d} \sum_{h=1}^{T^H} \left(C^G_{\omega,n,r,i} - C^{G,\sigma}_{\omega,n,r,i} + C^{G,\tau}_{\omega,n,r,i} \right) q^G_{\omega,n,r,i,d,h} \Big] \\
+ \sum_{r,r'\in R, r\neq r'} C^L_{\omega,r,r'} k^L_{\omega,r,r',i} + \sum_{r\in R, d\in T^D} \Upsilon_{i,d} \sum_{h=1}^{T^H} C^U q^U_{\omega,r,i,d,h} \Bigg\}
\end{aligned}$$

$$\text{s.t. } k^G_{\omega,n,r,i,1} \leq \bar{B}_{n,r,i}; \quad \forall \omega\in\Omega; n\in N; r\in R; i\in T^I \qquad (2)$$

$$k^G_{\omega,n,r,i,a} = k^G_{\omega,n,r,i-1,a-1} - k^E_{\omega,n,r,i-1,a-1}; \qquad (3)$$
$$\forall \omega\in\Omega; n\in N; r\in R; i\in T^I, i\geq 2; a=2,\ldots,A_n$$

$$\sum_{n\in N^\rho} \sum_{a=1}^{A_n} k^G_{\omega,n,r,i,a} \geq \rho_i; \quad \forall \omega\in\Omega; i\in T^I \qquad (4)$$

$$K_{\omega,i} \geq 0; \quad \forall \omega \in \Omega; i \in T^I \tag{5}$$

$$K_{\omega,i} = K_{\omega',i}; \quad \forall \omega \in \Omega; i \in T^I; \omega' \in \bar{\omega}_i \tag{6}$$

$$\sum_{n \in N} q^G_{\omega,n,r,i,d,h} + q^D_{\omega,r,i,d,h} - q^C_{\omega,r,i,d,h} + q^U_{\omega,r,i,d,h} \tag{7}$$
$$+ \sum_{r' \in R, r' \neq r} \left(q^L_{\omega,r',r,i,d,h} - q^L_{\omega,r,r',i,d,h} \right) = L_{\omega,r,i,d,h};$$
$$\forall \omega \in \Omega; n \in N; r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H$$

$$0 \leq q^G_{\omega,n,r,i,d,h} \leq \phi_{\omega,n,r,i,d,h} \sum_{a=1}^{A_n} k^G_{\omega,n,r,i,a}; \tag{8}$$
$$\forall \omega \in \Omega; n \in N; r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H$$

$$-\delta_n \sum_{a=1}^{A_n} k^G_{\omega,n,r,i,a} \leq q^G_{\omega,n,r,i,d,h} - q^G_{\omega,n,r,i,d,h-1} \leq \delta_n \sum_{a=1}^{A_n} k^G_{\omega,n,r,i,a}; \tag{9}$$
$$\forall \omega \in \Omega; n \in N; r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H$$

$$-\sum_{i' \leq i} k^L_{\omega,r,r',i'} \leq q^L_{\omega,r,r',i,d,h} \leq \sum_{i' \leq i} k^L_{\omega,r,r',i'}; \tag{10}$$
$$\forall \omega \in \Omega; r, r' \in R, r' \neq r; i \in T^I; d \in T^d; h = 1, \dots, T^H$$

$$q^S_{\omega,r,i,d,h} = q^S_{\omega,r,i,d,h-1} - q^D_{\omega,r,i,d,h} + \zeta q^C_{\omega,r,i,d,h}; \tag{11}$$
$$\forall \omega \in \Omega; r \in R; i \in T^I; d \in T^d; h = 2, \dots, T^H$$

$$q^S_{\omega,r,i,d,0} = \frac{1}{2} \eta \sum_{i' \leq i} k^S_{\omega,r,i}; \quad \forall \omega \in \Omega; r \in R; i \in T^I; d \in T^d \tag{12}$$

$$q^S_{\omega,r,i,d,T^H} = \frac{1}{2} \eta \sum_{i' \leq i} k^S_{\omega,r,i}; \quad \forall \omega \in \Omega; r \in R; i \in T^I; d \in T^d \tag{13}$$

$$0 \leq q^S_{\omega,r,i,d,h} \leq \eta \sum_{i' \leq i} k^S_{\omega,r,i}; \quad \forall \omega \in \Omega; r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H \tag{14}$$

$$0 \leq q^C_{\omega,r,i,d,h}, q^D_{\omega,r,i,d,h} \leq \sum_{i' \leq i} k^S_{\omega,r,i}; \tag{15}$$
$$\forall \omega \in \Omega, r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H$$

$$0 \leq q^U_{\omega,r,i,d,h} \leq L_{\omega,r,i,d,h}; \tag{16}$$
$$\forall \omega \in \Omega; n \in N; r \in R; i \in T^I; d \in T^d; h = 1, \dots, T^H.$$

Objective function (1) minimizes expected discounted cost. The objective function includes seven cost components. The first is the cost of investing in new generation capacity. New generation capacity that is added during investment-epoch i is $a = 1$ investment epochs old at the end of the epoch. Thus, new capacity is given by $k^G_{\omega,n,r,i,1}$. The second term in (1) is the cost of retiring generating capacity. The third term is generator-maintenance costs. The fourth term is the cost of investing in energy storage. The fifth term is generator-operation costs. The sixth term in (1) is the cost of adding transmission capacity. The final term is the cost of unserved load.

The model has two types of constraints—(2)–(6) and (7)–(16) pertain to investment and operating decisions, respectively. Constraints (2) impose limits on generation investments. Constraints (3) define the time evolution of the amount of generating capacity of different ages. Constraints (4) impose capacity-based RPS requirements. Constraints (5) impose non-negativity on the investment variables. Constraints (6) are non-anticipativity constraints. These impose the structure of the scenario tree on the decisions. This is done by ensuring that decisions that are made during each investment epoch are not dependent on future scenario realizations.

Constraints (7) impose the load-balance requirement during each operating period. Constraints (8) impose capacity limits on generator, which are defined based on a capacity factor, $\phi_{\omega,n,r,i,d,h}$. For most dispatchable generation technologies these capacity factors equal 1. However, for weather-dependent renewables the capacity factors vary across operating periods and can be less than 1, to represent the impacts of weather conditions. Constraints (9) impose ramping limits on generators. Constraints (10) impose transmission-capacity limits.

Constraints (11)–(15) pertain to the operation of energy storage. Constraints (11) define the time evolution of the SOE of energy storage. Constraints (12) and (13) force energy storage to begin and end each day with a 50% SOE. This is a heuristic approach to attaching carryover value to stored energy from one day to the next [20]. Constraints (14) and (15) impose energy and power limits on energy storage.

Constraints (16) limit the amount of unserved energy in each operating period to be no greater than demand.

3.3 Unit-Commitment Model

Following convention, we formulate our unit-commitment model as a mixed-integer linear optimization problem [21–24].

3.3.1 Model Notation

We define the following model notation. Some of the notation that is common with the capacity-expansion model (*i.e.*, R, C^U, η, and ζ) is not repeated here.

Sets and Set-Related Parameters

$\mathscr{G}$	set of generators.
$\mathscr{G}(r)$	set of generators that are in zone r.
$\mathscr{G}^O(r)$	set of non-dispatchable generators that are in zone r.
$\mathscr{S}$	set of energy-storage units.
$\mathscr{S}(r)$	set of energy-storage units that are in zone r.
$\mathscr{H}$	set of hours.

Parameters

c_g	variable generation cost of generator g (\$/MWh).
c_g^{SU}	start-up cost of generator g (\$/start-up).
c_g^{σ}	PTC for generator g (\$/MWh).
c_g^{τ}	carbon tax for production of generator g (\$/MWh).

$c_g^{\tau,\mathrm{SU}}$	carbon tax for generator g starting up (\$/start-up).
C^P	cost of unserved operating reserves (\$/MW-h).
$D_{r,h}$	hour-h load in zone r (MW).
$f_{r,r'}^+$	capacity of transmission line connecting zones r and r' (MW).
X_g^-	minimum output level of generator g when it is online (MW).
$X_{g,h}^+$	maximum hour-h output level of generator g when it is online (MW).
X_s^{PW}	power capacity of energy-storage-unit s (MW).
Δ_g	ramping limit of generator g (MW/h).
ξ^D	load-based operating-reserve requirement (p.u.).
ξ^O	operating-reserve requirement based on non-dispatchable generation (p.u.).

Decision Variables

$e_{s,h}^C$	hour-h power charged into energy-storage-unit s (MW).
$e_{s,h}^D$	hour-h power discharged from energy-storage-unit s (MW).
$e_{s,h}^P$	hour-h operating reserves provided by energy-storage-unit s (MW).
$e_{s,h}^S$	ending hour-h SOE of energy-storage-unit s (MWh).
$f_{r,r',h}$	hour-h power flow through transmission line connecting zones r and r' (MW).
$v_{r,h}^P$	hour-h unserved operating reserves in zone r (MW).
$v_{r,h}^U$	hour-h unserved load in zone r (MW).
$x_{g,h}^P$	hour-h operating reserves provided by generator g (MW).
$x_{g,h}$	hour-h power output of generator g (MW).
$y_{g,h}$	binary variable that equals 1 if generator g is online during hour h, and equals 0 otherwise.
$z_{g,h}$	binary variable that equals 1 if generator g is started at the beginning of hour h, and equals 0 otherwise.

3.3.2 Model Formulation

The unit-commitment model is formulated as:

$$\min \sum_{h\in\mathscr{H}} \left\{ \sum_{g\in\mathscr{G}} \left[\left(c_g - c_g^\sigma + c_g^\tau\right) x_{g,h} + \left(c_g^{\mathrm{SU}} + c_g^{\tau,\mathrm{SU}}\right) z_{g,h} \right] + \sum_{r\in R} \left(C^P v_{r,h}^P + C^U v_{r,h}^U\right) \right\} \tag{17}$$

$$\text{s.t.} \sum_{g\in\mathscr{G}(r)} x_{g,h} + \sum_{s\in\mathscr{S}(r)} (e_{s,h}^D - e_{s,h}^C) + \sum_{r'\in R, r'\neq r} (f_{r',r,h} - f_{r,r',h}) = D_{r,h} - v_{r,h}^U; \quad \forall r \in R; h \in \mathscr{H} \tag{18}$$

$$\sum_{g\in\mathscr{G}(r)\setminus\mathscr{G}^O(r)} x_{g,h}^P + \sum_{s\in\mathscr{S}(r)} e_{s,h}^P \geq \xi^D D_{r,h} + \xi^O \sum_{g\in\mathscr{G}^O(r)} x_{g,h} - v_{r,h}^P; \quad \forall r \in R; h \in \mathscr{H} \tag{19}$$

$$X_g^- y_{g,h} \leq x_{g,h}; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{20}$$

$$x_{g,h} + x^P_{g,h} \leq X^+_{g,h} y_{g,h}; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{21}$$

$$-\Delta_g \leq x_{g,h} - x_{g,h-1}; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{22}$$

$$x_{g,h} + x^P_{g,h} - x_{g,h-1} \leq \Delta_g; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{23}$$

$$z_{g,h} \geq y_{g,h} - y_{g,h-1}; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{24}$$

$$e^S_{s,h} = e^S_{s,h-1} + \zeta e^C_{s,h} - e^D_{s,h}; \quad \forall s \in \mathscr{S}; h \in \mathscr{H} \tag{25}$$

$$0 \leq e^C_{s,h} \leq X^{\mathrm{PW}}_s; \quad \forall s \in \mathscr{S}; h \in \mathscr{H} \tag{26}$$

$$0 \leq e^D_{s,h} + e^P_{s,h} \leq X^{\mathrm{PW}}_s; \quad \forall s \in \mathscr{S}; h \in \mathscr{H} \tag{27}$$

$$0 \leq e^S_{s,h} \leq \eta X^{\mathrm{PW}}_s; \quad \forall s \in \mathscr{S}; h \in \mathscr{H} \tag{28}$$

$$0 \leq e^P_{s,h} \leq e^S_{s,h} - e^D_{s,h}; \quad \forall s \in \mathscr{S}; h \in \mathscr{H} \tag{29}$$

$$-f^+_{r,r'} \leq f_{r,r',h} \leq f^+_{r,r'}; \quad \forall r, r' \in R, r' \neq r; h \in \mathscr{H} \tag{30}$$

$$0 \leq v^U_{r,h} \leq D_{r,h}; \quad \forall r \in R; h \in \mathscr{H} \tag{31}$$

$$x^P_{g,h} \geq 0; \quad \forall g \in \mathscr{G}; h \in \mathscr{H} \tag{32}$$

$$y_{g,h}, z_{g,h} \in \{0,1\}; \quad \forall g \in \mathscr{G}; h \in \mathscr{H}. \tag{33}$$

Objective function (17) minimizes the sum of generation costs and costs associated with any unserved load or operating reserves.

Constraints (18) impose load-balance requirements in each zone. Constraints (19) impose operating-reserve requirements. We assume that these requirements are the sum of portions of demand and scheduled production from non-dispatchable (*e.g.*, wind and solar) generators [25]. The rationale behind setting the operating reserves in this way is that the system should have sufficient flexibility to accommodate unanticipated loss of generation from non-dispatchable renewables. We allow only dispatchable generation units and energy storage to provide operating reserves.

Constraints (20) and (21) impose minimum- and maximum-generation limits, respectively, on each generator. The maximum-generation limit applies to the sum of energy and operating reserves, requiring that operating reserves can be provided without violating the capacity limit. To model renewables, each generating unit's maximum capacity can vary by hour. Constraints (22) and (23) impose ramping limits on generators. Constraints (23) ensure that each generator can provide its operating reserves without violating its ramping capability. Constraints (24) define each generator's start-up variables in terms of intertemporal changes in its online variables.

Constraints (25) define the time evolution of the SOE of each energy-storage unit. Constraints (26) and (27) impose power-capacity limits on charging and discharging, respectively, of each energy-storage unit. Constraints (27) ensure that the power-capacity limits of energy-storage units are not violated by serving operating reserves. Constraints (28) ensure that each energy-storage unit's SOE remains non-negative and below its energy capacity. Constraints (29) ensure that each energy-storage unit has sufficient stored energy to serve its operating-reserve commitment.

Constraints (30) impose transmission limits. Constraints (31) impose bounds and non-negativity on unserved load while (32) impose non-negativity on provided operating reserves. Constraints (33) ensure that the unit-commitment variables are binary.

3.4 Financial Analysis

We conduct our financial analysis of generation investments by computing the net operating profit that each generator earns on each day from the solution of the unit-commitment problem. Specifically, we define $\lambda_{r,h}$ and $\beta_{r,h}$ as the dual variables that are associated with (18) and (19), respectively, for hour h and zone r.[2] These dual variables represent hourly locational marginal prices for energy and reserves.

Based on the energy and reserve prices, generator g earns:

$$\sum_{h\in\mathscr{D}} \left[\left(\lambda_{r,h} - c_g + c_g^{\sigma} - c_g^{\tau}\right) x_{g,h} + \beta_{r,h} x_{g,h}^{P} - \left(c_g^{\mathrm{SU}} + c_g^{\tau,\mathrm{SU}}\right) z_{g,h} \right],$$

in profit from energy and reserve payments during day $\mathscr{D}$, where r denotes the zone in which generator g is located. A challenge in remunerating generators in markets that rely on centralized unit-commitment is that generators may operate at a net profit loss if they are paid based solely on energy and reserve prices. This complication arises because unit-commitment models are non-convex [26, 27]. Most wholesale electricity markets overcome this issue through make-whole payments, which are supplemental payments that are given to any generator that operates at a net profit loss if paid solely based on the energy and reserve prices [28]. The supplemental payment is equal to the profit loss. Taking account of make-whole payments, we compute generator g's total operating profits as:

$$\mathscr{P}_g = \sum_{\mathscr{D}} \max \Bigg\{ 0, \sum_{h\in\mathscr{D}} \left[\left(\lambda_{r,h} - c_g + c_g^{\sigma} - c_g^{\tau}\right) x_{g,h} + \beta_{r,h} x_{g,h}^{P} - \left(c_g^{\mathrm{SU}} + c_g^{\tau,\mathrm{SU}}\right) z_{g,h} \right] \Bigg\}. \quad (34)$$

We compute the ratio between each generator's total operating profits and its investment cost:

$$\mathscr{R}_g = \frac{\mathscr{P}_g}{\mathscr{I}_g},$$

where $\mathscr{I}_g$ is the investment cost of generator g, which is determined from the solution of (1)–(16). $\mathscr{R}_g$ represents the proportion of the generator's investment cost that is recovered from market revenues. One could conduct a back-of-the-envelope analysis of the financial viability of a generation investment by comparing $\mathscr{R}_g$ to the capital charge rate of the investment. If $\mathscr{R}_g$ is greater than the capital charge rate, one would conclude that the investment is viable, insomuch as its operating profits cover the estimated cost of financing the investment.

[2] Because (17)–(33) is a mixed-integer linear optimization problem, it does not have dual variables. Following standard industry practice, we obtain dual variables by fixing the binary variables in (17)–(33) to their optimal values and solving the resulting linear relaxation, which does have dual variables.

4 Case-Study Data

Our case study uses data for Electric Reliability Council of Texas (ERCOT) and is based on the work of Liu [29], which provides the complete data set. We summarize the case-study data. The case study assumes three zones (West, East, and South). The investment epochs begin in 2020 and occur at ten-year intervals, with 2040 being the final investment year. To account for inflation, all costs are measured in 2014 dollars.

4.1 Generation-and-Transmission-Expansion-Model Data

We model five generation technologies—wind, solar, nuclear-powered, and natural-gas- and coal-fired units—and an energy-storage technology. The system begins with a thermal-dominated design, consisting of 45 GW, 18 GW, 5 GW, and 4 GW of natural-gas- and coal-fired, nuclear, and wind generation, respectively.

The uncertainties that are modeled explicitly in the generation- and transmission-expansion model *via* scenarios are changes in investment and generation-fuel costs. Table 1 summarizes the range of baseline investment costs for wind and solar technologies during the three investment epochs. The scenarios in the planning model include cases in which investment costs vary from these baseline values by up to 5% and 7.5% in 2030 and 2040, respectively. This reflects technology-improvement uncertainty. Wind and solar are assumed to have zero operating cost.

Table 1: Baseline renewable-generation-technology investment costs in generation- and transmission-expansion model ($/kW) [30, 31]

Technology	2020	2030	2040
Wind	3737–3864	3440–3556	3350–3463
Solar	3164–3345	2990–3161	2603–2752

Table 2 summarizes the investment costs, the baseline range of operating costs in the three investment epochs, and the ramping factors of the non-renewable generation technologies. We model scenarios in which coal prices increase by up to 7% and 28% relative to their baseline values in 2030 and 2040, respectively. Scenarios allow for natural-gas prices to increase by up to 18% and 54% relative to their baseline values in 2030 and 2040, respectively. We model land-use limits on the installation of renewable resources [32], but not on other generating technologies.

We model a generic energy-storage technology with a capital cost of $2333/kW–$2362/kW, 20-hour discharge duration, and 80% roundtrip efficiency. This energy-storage technology is akin to pumped-hydroelectric or compressed-air energy storage. We focus on such energy-storage technologies because our model uses energy storage primarily for managing renewable curtailment and bulk generation shifting. Our model does not have sufficient spatial or temporal granularity to represent other energy-storage use cases (*e.g.*, distribution deferral or frequency regulation).

Table 2: Baseline investment and operating costs and ramping factors of non-renewable generation technologies in generation- and transmission-expansion model [30, 31]

Technology	Investment Cost ($/kW)	Operating Cost ($/MWh)			Ramping Factor (p.u.)
		2020	2030	2040	
Coal	3037–3164	25–26	27–28	28–29	0.29
Natural Gas	833–862	49–50	55–57	66–68	0.43
Nuclear	5437–5564	10–11	10–11	10–11	0.16

We use 30 days, which are selected from a single representative year using hierarchical clustering [19], to capture system operations between successive investment epochs. Weather conditions, which determine real-time solar and wind availabilities and demand patterns, are simulated using a vector-autoregression (VAR) model [33]. Residential electricity demands are simulated using a methodology that combines Monte Carlo simulation with physical models of residential devices [33, 34]. Commercial and industrial electricity demands are simulated using a time-series based model [35].

4.2 Unit-Commitment-Model Data

Once generation investments are determined in the first modeling step, natural-gas- and coal-fired capacity is divided into discrete generating units. This division is needed to model unit-commitment decisions. We do this division by using archetypal natural-gas- and coal-fired units, the minimum and maximum capacities of which are listed in Table 3. In each of the three investment epochs, we adjust the maximum output levels of the added units so that the added capacity can be divided evenly among an integer number of units. We adjust the maximum output levels to minimize the absolute difference between the adjusted maximum output level of each unit and the maximum output level of the corresponding archetypal unit. We scale the minimum-output levels of the units in proportion to the adjusted maximum output levels.

Table 3: Minimum and maximum output levels of archetypal natural-gas- and coal-fired generators in unit-commitment model (MW)

Technology	Minimum Output Level	Maximum Output Level
Natural Gas	168	600
Coal	224	800

Generator-operation costs, carbon taxes, PTCs, and ramping factors are the same in the unit-commitment model as they are in the generation- and transmission-expansion model. Start-up costs for natural-gas- and coal-fired generators are included in the unit-commitment model, with these costs being higher with a carbon tax (due to the associated fuel that is consumed). Nuclear units are assumed always to be operating at their maximum production levels.

We assume that hourly operating-reserve requirements are set equal to the sum of 3% of demand and 5% of total scheduled production from wind and solar units [25]. We set the cost of unserved load and operating reserves equal to $9000/MWh and fix the energy and operating-reserve prices to $9000/MWh during any hour with either load or operating-reserve curtailment. These pricing rules follow scarcity-pricing mechanisms that are employed in ERCOT.

We model unit-commitment decisions for each investment epoch, by simulating the full year from which the 30 operating days that are used in the generation- and transmission-expansion model are clustered. For sake of computational tractability, we conduct the simulation in a rolling-horizon fashion one day at a time, with a 48-hour optimization horizon. The 48-hour optimization horizon ensures that decisions at the end of each day take into account load conditions during the following day.

5 Case-Study Results

The three policy cases are calibrated to achieve the same target of 80% carbon reductions relative to the 2010 level by the end of 2040. An output-based carbon tax of $12/MWh and $6/MWh for coal- and natural-gas-fired units, respectively, achieves this goal. The goal can be achieved with PTCs of $30/MWh and $35/MWh for wind and solar, respectively, or RPS targets of at least 30 GW and 185 GW for 2030 and 2040, respectively.

Figure 1 summarizes the optimal generation mix that is built under each policy in the baseline scenario of the generation- and transmission-expansion model. Figure 1 shows that the policy choice has major impacts on the investments. The BAU case results in modest investment in natural-gas- and coal-fired generation during 2020, which is followed by attrition of these technologies as older units reach end-of-life. This natural-gas- and coal-fired capacity is replaced by nuclear and wind units.

A carbon tax results in investments that are closest to those in the BAU case. Unlike in the BAU case, a carbon tax sees no investment in and greater retirement of coal-fired capacity. Similarly, there is less investment during 2020 in and greater subsequent phase-out of natural-gas-fired units with a carbon tax. The BAU case results in 24 GW and 39 GW of coal- and natural-gas-fired capacity, respectively, in 2040 compared to 16 GW and 37 GW with a carbon tax. The lost fossil-fueled capacity in the carbon-tax case is replaced with nuclear investments (33 GW and 18 GW by 2040 in the carbon-tax and BAU cases, respectively).

The other two policy mechanisms yield very different investments relative to BAU. With a PTC, no new nuclear units are added and coal- and natural-gas-fired capacities in 2040 are 16 GW and 23 GW, respectively. These technologies are replaced with 67 GW of wind, 55 GW of solar, and 10 GW of energy storage. An RPS results in qualitatively similar investments, with 20 GW, 10 GW, 35 GW, 150 GW, and 18 GW of coal- and natural-gas fired, wind, solar, and energy-storage capacity in 2040.

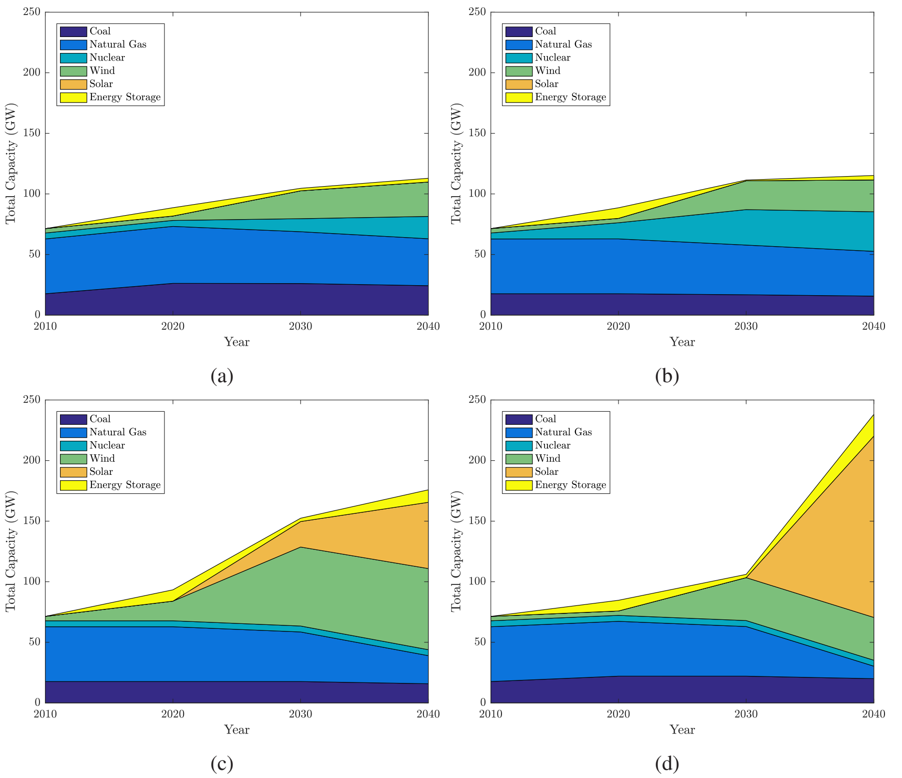

Fig. 1: Total installed capacities of generation and energy-storage technologies under (1a) BAU, (1b) carbon-tax, (1c) PTC, and (1d) policies in baseline scenario of the generation- and transmission-expansion model

Figure 2 summarizes the energy-production mix under each policy during each of the three representative years that are simulated using the unit-commitment model. The system achieves the same reliability level under all policies, with at least 99.99% of load being served. The energy mixes that are shown in Figure 2 follow the capacity mixes that are shown in Figure 1. The BAU case results in the energy mix being divided between coal-fired, nuclear-powered, and wind generation. A carbon tax results in coal-fired generation largely being eliminated in favor of nuclear output. A PTC or RPS results in very high use of renewable generation—more than 81% of energy is produced by wind and solar in the PTC and RPS cases in 2040 as opposed to less than 29% in the other cases.

Table 4 summarizes the resulting cost of investing in and operating the system over the thirty-year optimization horizon of our case study in the baseline scenario of the generation- and transmission-expansion model. The table breaks the costs into several categories. The first three sets of values provide the cost of investing in, maintaining, and decommissioning capacity in each investment epoch. These costs are obtained from the generation- and transmission-expansion model. The next three

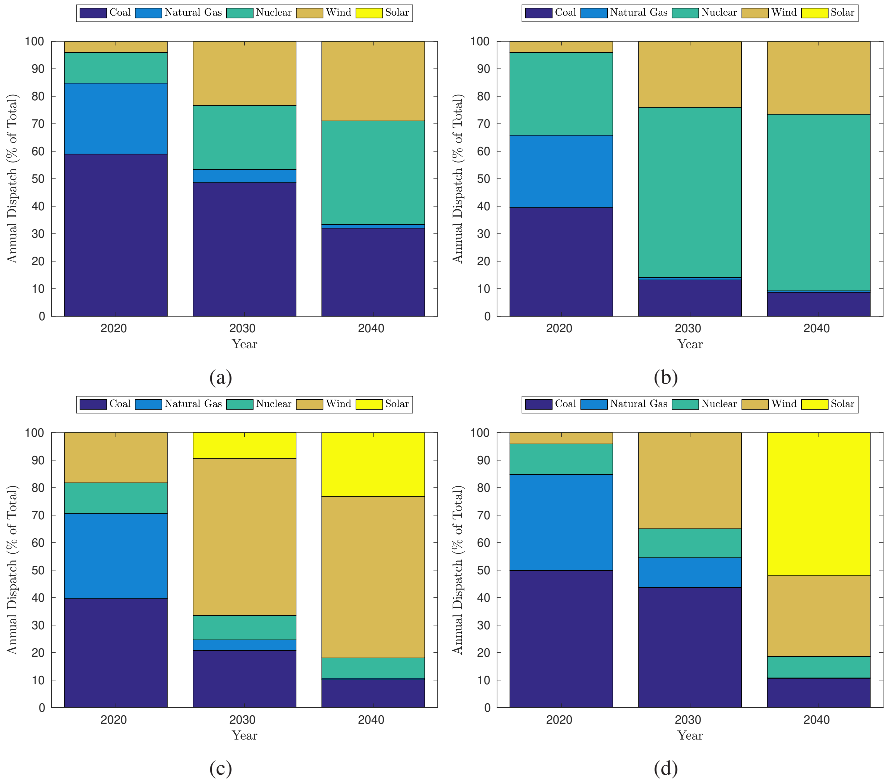

Fig. 2: Dispatch in each representative year of generation technologies under (2a) BAU, (2b) carbon-tax, (2c) PTC, and (2d) RPS policies in baseline scenario of the generation- and transmission-expansion model

sets of values provide the annual system-operation cost in each of the representative years, and are obtained from the unit-commitment model. The PTC results in negative operating costs because the PTC that is paid to wind and solar units outweigh the operating costs of the balance of the generator fleet.

The next row of the table gives for each policy the total gross cost, which is the sum of the investment costs and ten times the operating costs (which reflects each operating year representing the ten-year period that follows each investment epoch). The following row of the table gives the cost adjustment that arises from the policy mechanism that is employed. For a carbon tax, the tax revenue that is collected (which is reflected in the operating cost) is subtracted from the total gross cost. This is because the carbon tax reflects a wealth transfer from fossil-fueled generators to the government. As such, the tax is not a welfare loss or gain. The PTC involves a policy-related cost adjustment also, which is the cost of the subsidy. The final two rows of Table 4 report net system cost, which is total gross cost and any policy-related cost-adjustments. The net costs show that the policies differ in how efficiently they

Table 4: Breakdown of total investment and operating costs under different policies in baseline scenario of the generation- and transmission-expansion model

	BAU	Carbon Tax	PTC	RPS
Investment Cost [$ Billion]				
2020	69.49	95.83	99.94	58.09
2030	102.11	143.39	187.28	106.96
2040	67.65	67.27	104.66	179.45
Operating Cost [$ Billion/Year]				
2020	11.43	12.81	8.32	12.20
2030	3.87	2.64	−2.36	4.00
2040	1.60	1.24	−2.45	0.49
Total Gross Cost [$ Billion]	408.21	473.46	427.00	511.41
Policy-Related Cost Adjustment [$ Billion]	0.00	−35.84	218.87	0.00
Net Cost				
Aggregate [$ Billion]	408.21	437.62	645.87	511.41
Per-MWh [$/MWh]	33.34	35.74	52.75	41.77

achieve carbon reductions. A carbon tax and PTC are the most and least efficient, respectively, increasing system costs 7% and 60% relative to BAU.

Table 5 summarizes the financial viability of generation investments. It reports for each generating technology the value of $\mathscr{R}_g$ during each investment epoch. A value that has a $(+)$ superscript indicates that particular technology has net capacity additions during the corresponding investment epoch. The value that is reported for a technology that has net capacity additions is the ratio between the average profits that are earned during the corresponding representative operating year by units that are added and their average investment costs. As such, these ratios can be compared to the capital charge rate to determine the financial viability of an investment.

A value in Table 5 that has a $(-)$ superscript indicates that a technology has net capacity retirements during the corresponding investment epoch. For technologies with net retirements or no net capacity changes, the values that are reported in the table represent the value of $\mathscr{R}_g$ for a hypothetical capacity investment, which is based on the average operating profit of the technology during the corresponding representative operating year. As such, these values can be used to gauge the financial viability of adding a marginal unit of such technologies. $\mathscr{R}_g$ are not reported for solar in the BAU and carbon-tax cases, because this technology is not used under these policies.

We do not compare the values in Table 5 to any particular value. Rather, we focus on trends in the value of $\mathscr{R}_g$ between investment epochs and policies. The reason for this is that the values in Table 5 are artifacts of our modeling assumptions. For instance, our systems are designed to achieve a very high reliability of at least 99.99%. However, the value of lost load is capped at $9000/MWh. These values do not necessarily reflect society's true willingness to pay for reliable electricity service.

$\mathscr{R}_g$ tends to be higher for technologies that are built compared to those that are retired. This follows the intuition behind the stylized cost-recovery model underlying the design of wholesale electricity markets [3]. Investments and retirements are signaled in a restructured market by revenues that existing or candidate capacity earn or can earn in the market. An exception to the trend in $\mathscr{R}_g$ is solar investment under an

Table 5: $\mathscr{R}_g$ of each generation technology during each investment epoch

	Coal	Natural Gas	Nuclear	Wind	Solar
BAU					
2020	$6.2^{(+)}$	$1.0^{(+)}$	5.9	5.8	n/a
2030	$3.2^{(-)}$	$0.3^{(-)}$	$4.4^{(+)}$	$3.9^{(+)}$	n/a
2040	$1.6^{(-)}$	$0.0^{(-)}$	$3.6^{(+)}$	$4.1^{(+)}$	n/a
Carbon Tax					
2020	5.0	$1.6^{(+)}$	$7.0^{(+)}$	6.5	n/a
2030	$0.9^{(-)}$	$0.4^{(-)}$	$3.9^{(+)}$	$3.8^{(+)}$	n/a
2040	$0.7^{(-)}$	$0.1^{(-)}$	$3.5^{(+)}$	$3.5^{(+)}$	n/a
PTC					
2020	6.3	0.4	6.0	$8.2^{(+)}$	n/a
2030	2.6	$0.0^{(-)}$	3.2	$3.8^{(+)}$	$3.0^{(+)}$
2040	$1.2^{(-)}$	$0.1^{(-)}$	2.1	$3.0^{(+)}$	$2.3^{(+)}$
RPS					
2020	$6.4^{(+)}$	0.6	6.1	5.4	n/a
2030	$5.2^{(-)}$	$0.2^{(-)}$	5.4	$4.2^{(+)}$	n/a
2040	$0.4^{(-)}$	$0.0^{(-)}$	1.7	$1.5^{(-)}$	$0.4^{(+)}$

'$^{(+)}$' indicates technologies that have net capacity additions. '$^{(-)}$' indicates technologies that have net capacity retirements.

RPS. Such units earn near-zero profits, despite having no operating cost. The reason for this is that the extremely high penetration of solar that is achieved with an RPS by 2040 results in energy prices being suppressed during the middle of the day when solar production peaks. Although energy prices under a PTC experience a similar trend, the subsidy mitigates this impact. As such, solar units have higher values of $\mathscr{R}_g$ with a PTC relative to with an RPS. One means of providing renewable generators with a supplemental revenue stream with an RPS, which is used in a number of jurisdictions, is to create a supplemental market for renewable energy certificates [9]. These certificates pay renewable generators for their contribution toward meeting the RPS.

Significant nuclear investments are undertaken in the BAU and carbon-tax cases. These units have relatively high values of $\mathscr{R}_g$, with a capacity-weighted average of 4.2 over the investment epochs in the BAU and carbon-tax cases. Nuclear capacity is not added in the PTC and RPS cases. Nevertheless, it is important for these units to earn sufficient profit for their ongoing operation and maintenance to remain financially viable. The RPS policy achieves this target whereas the PTC falls short with a capacity-weighted average value over the investment epochs of $\mathscr{R}_g = 3.7$. This low value of $\mathscr{R}_g$ is due largely to the PTC suppressing energy prices, because the subsidy appears as a negative cost in (17).

6 Conclusions

The literature and past experience (*e.g.*, with cap-and-trade-based SO_2 markets) indicates that market-based policies can address climate change more efficiently than subsidies or technology mandates can. Despite this knowledge, many jurisdictions are employing less efficient policies. In some cases, these policy choices are politically driven. The extant literature indicates that high renewable-energy penetrations can create or exacerbate price-formation and market-design problems.

Our case study demonstrates that there are significant differences in the efficiency of meeting carbon-reduction targets through different policies. A carbon tax is most efficient, which follows from basic economic principles that internalizing the cost of an externality can align private and societal incentives efficiently. Climate-change-related policies that are used most commonly—PTC and RPS—are considerably less efficient. Using a PTC in our case study is eight times as costly as employing a carbon tax. Indeed, the taxation that is needed to fund the subsidy can create other societal losses that our case study does not capture. Our case study shows also that policy choices can yield capacity and cost distortions that can impact price formation in wholesale electricity markets and harm the financial viability of capacity investments.

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