Decarbonization and Electrification in the Long Run*

Stephen P. Holland† Erin T. Mansur‡ Andrew J. Yates§

November 18, 2022

Abstract

We study decarbonization and electrification using a long-run model that captures crucial aspects of the electricity industry such as time-varying demand, intermittency of renewables, and intertemporal optimization of storage. Several theoretical possibilities differ in surprising ways from short-run intuition: A carbon tax can increase electricity consumption; cheaper renewables can increase carbon emissions; cheaper storage can decrease renewable capacity; and an increase in electricity demand (e.g., electrification) can decrease emissions. Calibrating the model to the U.S. finds a carbon price of $150 or more essentially eliminates carbon emissions. For modest decarbonization, a renewable subsidy dominates a nuclear subsidy; the reverse occurs for an ambitious decarbonization goal. Transmission expansion can aid decarbonization, but policies promoting storage do not. We calculate long-run marginal emissions. Electrifying light duty vehicles increases electricity-sector emissions by 23-27% if vehicles are charged at night, but could *decrease* electricity-sector emissions if vehicles are charged during the day.

JEL Codes: H23, Q4, Q53, Q54

Keywords: Long run marginal emissions, climate, electric vehicles, environmental policy

*We would like to thank Nicholas Taborsky and Robert Burnham for research assistance. We would like to thank Jim Bushnell, seminar participants at the University of Bern Energy Economic Workshop, the University of Wisconsin Madison, the University of Chicago-EPIC, Cornell University, the NBER Summer Institute, Universidad Carlos III de Madrid, Toulouse School of Economics, Paris School of Economics, London School of Economics, University of Mannheim, University of Virginia, and EPIC-China for helpful comments and suggestions.

†University of North Carolina at Greensboro and NBER. Email: `sphollan@uncg.edu`.

‡Tuck School of Business at Dartmouth and NBER. Email: `erin.mansur@dartmouth.edu`.

§University of North Carolina at Chapel Hill. Email: `ajyates@email.unc.edu`.

1 Introduction

Addressing the problem of global climate change will require radical transformations of large segments of the economy. Fundamentally, society needs to reassess what we make and how we make it across all industries. One key industry, electricity, currently accounts for about a third of U.S. carbon emissions and for similar proportions throughout the world. Yet, instead of shrinking the profile of this heavily polluting industry, most plans for a decarbonized economy call for dramatically expanding this sector by electrifying everything (*e.g.,* transportation, heating, and industrial processes), while at the same time decarbonizing electricity generation. Technological advances and cost declines in wind and solar energy have fueled optimism about the potential for decarbonized electricity generation. Nuclear technology is an alternative zero-carbon energy source, and advances in electricity storage technologies may hold transformative potential. In addition, advances in electric vehicles, heat pumps, electrolytic hydrogen feedstocks, and heating technologies (electromagnetic, induction, infrared and ultraviolet) hold promise for electrification of other sectors.[1] In short, the electricity sector of the future may look nothing like the electricity grid of today.

This paper constructs a framework for analyzing a completely transformed electricity grid with a long-run competitive equilibrium model of electricity consumption, generation, investment, and storage.[2] A key distinguishing feature of our model is that entry and exit for all technologies respond to the interconnected feedback effects from technological innovation, climate policy, and electrification, free from the hysteresis of legacy investments and historical accidents.[3] As such, our framework provides a unique perspective on decarbonization and electrification policies, and the interaction between them.

[1]See IEA (2019) and Hasanbeigi et al. (2021) on technologies for electrification of industrial processes.

[2]Our model is based on Borenstein (2005) and Borenstein and Holland (2005), which analyzed the long-run benefits of real-time pricing of electricity. We extend the original model, still assuming real-time pricing, to include intermittent renewables and storage. See also Ambec and Crampes (2021), Gambardella et al. (2020), and Holland and Mansur (2008) for studies of the environmental effects of real-time pricing.

[3]A substantial literature analyzes entry and exit from the existing electricity grid. See for example Gillingham et al. (2021), Stock and Stuart (2021), Borenstein and Kellogg (2022) and Palmer et al. (2011)

Some long-run theoretical possibilities can differ in surprising ways from their short-run analogs.[4] First, although carbon pricing decreases carbon emissions, we show that carbon pricing can *increase* overall electricity consumption in the long run if it induces sufficient entry of low-cost clean technologies. Second, a decrease in the cost of renewables can *increase* carbon emissions if the renewables crowd out a zero-emission technology such as nuclear. Third, cheaper storage can *decrease* renewable capacity. Intuitively, storage can benefit renewables by increasing demand in low-price periods but can harm renewables by increasing supply in high-price periods. Finally, in contrast to short-run incremental emissions from electrification, which are positive or zero, long-run incremental emissions can be *negative* if electricity usage in some periods induces entry of renewables which offset fossil generation in other periods. In this case, electrification can actually facilitate decarbonization of the electricity grid. These theoretical possibilities illustrate the importance of our long-run perspective.

To quantify these long-run effects, we calibrate our model for each of thirteen EIA electricity regions using observed hourly demand and corresponding hourly solar and wind generation for 2019. This calibration is distinguished in both scope and scale. Most analyses with national scope analyze a limited set of representative time periods (Gillingham et al. (2021), Palmer et al. (2011), Stock and Stuart (2021)) while analyses with richer demand and renewable representation focus on a single region or Independent System Operator (ISO) (Gowrisankaran et al. (2016), Elliot (2021), Imelda et al. (2018)). Implicitly, we use observed data as draws from the complex, empirical joint distribution of shocks to demand as well as wind and solar availability. This provides realistic approximations of the underlying variation and correlations between demand and renewable availability for the entire contiguous U.S.[5]

In addition to wind and solar, our calibration includes nuclear power, two natural gas powered technologies, and battery storage. All capital cost estimates are for the near future, and because these costs are highly uncertain, we consider a broad range of sensitivity analyses

[4] Large multi-sectoral models such as the National Energy Modeling System (NEMS) provide a comprehensive basis for policy analysis but do not allow for theoretical insights (Palmer et al. (2011), Gillingham et al. (2021), Stock and Stuart (2021), and Gagnon and Cole (2022)).

[5] We explore the effects of a reduced number of representative time periods in Online Appendix O.A.2.

and assumptions about technological progress. According to our calculations in Section 3, new coal plants are dominated by natural gas plants. Because there are no fixed inputs in the long run, we do not analyze any existing plants.[6]

The calibrated model allows us to explore multiple decarbonization pathways. Carbon pricing reduces long-run carbon emissions by inducing a mixture of renewable and nuclear generation, but, consistent with our theoretical results, need not necessarily reduce electricity consumption. We find almost complete decarbonization with a carbon price of $150 per metric ton of CO_2. Reductions in costs of zero-carbon technologies, whether policy induced or through technological progress, can also decarbonize electricity. We find that reductions in costs of renewables lead to substantial reductions in emissions.[7] Reductions in nuclear costs can also decarbonize electricity, but we find large threshold effects: cost declines only contribute to decarbonization if they are 50% or more.[8] Expanding transmission capacity or battery capacity can also potentially contribute to decarbonization by shifting zero-carbon electricity from low- to high-value locations or times.[9] We find that transmission expansion can result in substantial decarbonization if renewable costs also fall. Cheaper battery storage has ambiguous effects on carbon emissions, consistent with our theoretical findings. Overall we find that batteries do not contribute much to decarbonization unless they become practically free.

Our framework allows a comprehensive welfare analysis of policies that support these decarbonization pathways.[10] We find substantial welfare gains to carbon pricing, but a

[6]Holland et al. (2020) document the decline in coal-fired generation and Linn and McCormack (2019), Davis et al. (2021), and Heutel (2011) examine the retirement decisions of coal plants.

[7]Gowrisankaran et al. (2016) estimate large benefits for solar energy in southeastern Arizona, and Callaway et al. (2018) estimate displaced emissions by wind and solar generation. Ambec and Crampes (2019) and Helm and Mier (2019) present theoretical models of investment in intermittent renewables. See also Weber and Woerman (2022), Eisenack and Mier (2019), Pommeret and Schubert (2021) and Junge et al. (2022). Reguant (2019) studies the efficiency and distributional benefits of various renewable promoting policies in California.

[8]Davis and Hausman (2016) study the effects of nuclear power plant closure. Jenkins et al. (2018) analyze the benefits of using nuclear power plants to reduce renewable curtailment with fixed renewable capacity. In our results, nuclear power reduces renewable capacity and generation.

[9]The literature on the benefits of transmission is relatively small. See Cicala (2022), Fell et al. (2021), McCalley et al. (2012), Brown and Botterud (2021), and LaRiviere and Lyu (2022). Battery storage has been widely studied but is computationally intensive so most studies focus on a single region. See Karaduman (2020), Butters et al. (2021), Junge et al. (2021), and Shrader et al. (2021). See Andres-Cerezo and Fabra (2022) for an analysis of storage and market power.

[10]Cost-minimizing grid dispatch models may allow for complex ramping and transmission constraints, but do not generally analyze welfare issues (Hawkes (2014), Raichur et al. (2015)).

significant proportion of these gains can be realized by subsidizing zero-carbon technologies instead. If the Social Cost of Carbon (SCC) is low, the second-best policy is to subsidize renewables. However, if the SCC is very high, the second-best policy is to subsidize nuclear power. We find relatively modest welfare gains to subsidizing battery storage.[11]

Electrification will affect renewable capacity, and our theoretical results show that this may help or hinder decarbonization. To study this relationship, we consider the effects of both small and large changes in electricity load on the long-run equilibrium. For small load shocks, there are generally three types of outcomes across hours and locations. First, the shock may simply increase natural gas capacity so that the long-run marginal emissions (LRMEs) are approximately the natural gas power plant emissions rate. Second, the shock may decrease solar capacity so that LRMEs are greater than the natural gas rate. Third, the shock may increase solar capacity so that LRMEs are less than the natural gas rate and may even be zero or negative with lower renewable costs.[12]

The effects of large changes in electricity load on emissions also depend on the hours when the electricity is used.[13] For transportation, this means the hours the electric vehicles (EVs) are charged, *i.e.,* the charging profile. We find that with a convenient, nighttime charging profile and our baseline, electrifying 100% of car vehicle miles traveled (VMT) would result in a 23% increase in electricity-sector carbon emissions, with incremental emissions exceeding the natural gas emissions rate.[14] However, with a different charging profile, EV charging can result in very low additional emissions. Remarkably, if renewable costs are lower, a charging profile in which charging occurs exclusively in mid-day has *negative* additional emissions. In other words, charging EVs with this profile can completely decarbonize passenger vehicle transportation and reduce carbon emissions from the electricity sector, because it induces

[11]Butters et al. (2021) calculate larger benefits from battery storage for a fixed renewable capacity.

[12]A large literature estimates short-run marginal emissions using either econometrics (Holland and Mansur (2008); Holland et al. (2016); Graff Zivin et al. (2014); Siler-Evans et al. (2012); Fell and Kaffine (2018)) or grid dispatch models (Raichur et al. (2015)). Using dispatch models, Hawkes (2014) estimates LRMEs for Britain, and Gagnon and Cole (2022) estimate LRMEs for the U.S. Holland et al. (2022) shows conditions under which short-run marginal emissions estimates can be used to analyze emission over a 10-15 year time frame.

[13]Many studies analyze the effects of the timing of electrification and efficiency in the short run (see Boomhower and Davis (2020)).

[14]Holland et al. (2022) estimate that about half the emissions reduced in the transportation sector from partial electrification would be offset by increased electricity sector emissions.

a dramatic entry of renewables. The socially optimal charging profile balances emissions reductions with private surplus losses and reduces total carbon emissions substantially.

EV charging will depend on the location of charging stations. Although we do not explicitly model the build out of EV charging stations, our results imply that charging stations that enable EV users to charge easily during the day (*e.g.,* at work and shopping locations) will likely result in much lower long-run incremental carbon emissions than charging stations that facilitate charging at night (*e.g.,* at apartment buildings and on-street parking locations). This highlights the importance of locational and temporal heterogeneity in electrification policy and of investment incentives; factors which our framework is uniquely suited to analyze.

Climate policy has reached a crucial juncture. Despite increasing recognition of urgency, the path forward is unclear. Carbon pricing, widely recognized as an efficient policy, has not been universally adopted and may not have the transformative potential to remedy all the market failures associated with climate change. Other policies tend to promote particular technologies, such as storage or renewables, without clear guidance on the interconnected incentives created by the policies. Our analysis offers a novel perspective on decarbonization and electrification policies in a comprehensive framework.

2 The model

Consider a long-run model in which electricity consumption, generation, storage, and generation capacity are all endogenous. Because electricity demand and renewable availability vary across time, we model a long-run competitive equilibrium with T periods, (*e.g.,* hours) in which all agents have perfect foresight. In a given period t, electricity consumption is Q_t, and the hourly benefit (gross consumer surplus) is $U_t(Q_t)$ where $U_t' > 0$ and $U_t'' < 0$. The demand function, D_t, is the inverse function of U_t' defined by $U_t'(D_t(p)) \equiv p$.[15]

Electricity can be generated from I different technologies, each of which produces electricity at a constant operating cost up to some limit based on the installed capacity. Let K_i

[15] Implicitly, this assumes real-time pricing of electricity, zero cross-price elasticities, and indifference to the source of generation.

be technology i's capacity, which has capital costs r_i per unit. Each technology has an hourly capacity factor $f_{it} \in [0,1]$ so that generation, q_{it}, from technology i in hour t must satisfy $q_{it} \leq f_{it}K_i$. The hourly capacity factors are exogenous and allow for intermittent renewable generation ($f_{it} \leq 1$) or dispatchable generation ($f_{it} = 1$ for all t).[16] Let c_i be the constant operating cost for technology i where the technologies are ordered such that $c_i \leq c_{i+1}$. Each technology may or may not have external costs, *e.g.,* carbon emissions, associated with its use. Accordingly, define $\beta_i \geq 0$ as the carbon emissions intensity of technology i.

Electricity may be transferred across time using a storage technology, e.g., a battery. Let b_t be the net charge added to the battery in hour t where $b_t < 0$ indicates withdrawals from the battery. The state of the battery, S_t, depends on net charges to the battery and evolves according to $S_t = S_{t-1} + b_t$.[17] Battery storage cannot exceed the maximum battery capacity $\bar{S}$, so the state of the battery must satisfy $0 \leq S_t \leq \bar{S}$. The battery capacity is endogenous in the model and has capital costs r_s per unit. Electricity balance in each hour then requires that $Q_t + b_t \leq \sum_i q_{it}$, i.e., consumption plus net battery charge cannot exceed electricity generation from all sources.

To characterize the long-run competitive equilibrium, we use the planner's problem:

$$\max_{Q_t, q_{it}, b_t, S_t, K_i, \bar{S}} \sum_t [U_t(Q_t) - \sum_i c_i q_{it}] - \sum_i r_i K_i - r_s \bar{S}, \tag{1}$$

subject to all the constraints. This is a straightforward constrained optimization problem, albeit with a large number of choice variables.[18] To characterize the optimum, we use the pseudo-Hamiltonian, H_t, to write the Lagrangian, $\mathcal{L}$, for (9) as:

$$\mathcal{L} \equiv \sum_t H_t - \sum_i r_i K_i - r_s \bar{S}. \tag{2}$$

[16]Alternatively we might have $f_{it} < 1$ for dispatchable generation to account for forced outages.

[17]This assumes that storage is "perfect", *i.e.,* there are no conversion losses from charging or discharging the battery and the battery state does not decay over time.

[18]There are $(3 + I)T + I + 1$ choice variables. Hourly periods over a year (8760 hours) and five technologies imply over 70,000 choice variables.

Here H_t is defined by:

$$H_t \equiv U_t(Q_t) - \sum_i c_i q_{it} + p_t[\sum_i q_{it} - Q_t - b_t] + \sum_i \lambda_{it}[f_{it} K_i - q_{it}] + \phi_t[S_{t-1} + b_t - S_t] + \mu_t[\bar{S} - S_t],$$

where p_t, λ_{it}, ϕ_t, and μ_t are all non-negative shadow values of the relevant constraints.[19]

The Kuhn-Tucker first-order conditions include

$$
\begin{array}{lllll}
Q_t \geq 0 & d\mathcal{L}/dQ_t = U_t'(Q_t) - p_t \leq 0 & \forall t & C.S. & (3) \\
q_{it} \geq 0 & d\mathcal{L}/dq_{it} = -c_i + p_t - \lambda_{it} \leq 0 & \forall i, t & C.S. & (4) \\
 & d\mathcal{L}/db_t = -p_t + \phi_t = 0 & \forall t & & (5) \\
S_t \geq 0 & d\mathcal{L}/dS_t = \phi_{t+1} - \phi_t - \mu_t \leq 0 & \forall t & C.S. & (6) \\
K_i \geq 0 & d\mathcal{L}/dK_i = \sum_t \lambda_{it} f_{it} - r_i \leq 0 & \forall i & C.S. & (7) \\
\bar{S} \geq 0 & d\mathcal{L}/d\bar{S} = \sum_t \mu_t - r_s \leq 0 & & C.S., & (8)
\end{array}
$$

where $C.S.$ indicates a complementary slackness condition.[20] The condition [3] implies that the marginal benefit equals the shadow value p_t if electricity consumption is positive. From here on p_t is called the *electricity price*.

The following lemmas help characterize the optimum. All proofs are in the Appendix. The first lemma characterizes supply from each technology.

Lemma 1. *If $c_i > c_{i'}$ and $q_{it} > 0$, then $q_{i't} = f_{i't} K_{i'}$.*

This lemma shows that if generation from a given technology is positive, then any technology with a lower operating cost must be generating at available capacity. The hourly industry supply curve is then a step function with the step widths determined by the installed capacity and the hourly capacity factors.

The next lemma provides a formula for calculating the electricity price in hour t conditional on battery usage and the installed capacities.

Lemma 2. *If $\sum_i f_{it} K_i > b_t$, then $p_t = \min_i \{\max\{c_i, U_t'(\sum_{i' \leq i} f_{i't} K_{i'} - b_t)\}\}$.*

[19] H_t is not technically the Hamiltonian of (9) because it treats the adjoint variable differently.

[20] Additional conditions are the constraints and their complementary slackness conditions.

This lemma is illustrated graphically in Figure O.A.1, which shows the electricity price is determined by the intersection of the demand curve and the step function supply curve.

The third lemma characterizes the optimal battery usage.

Lemma 3. *If $S_t = 0$, then $p_t \geq p_{t+1}$. If $0 < S_t < \bar{S}$, then $p_t = p_{t+1}$. If $S_t = \bar{S}$, then $p_t \leq p_{t+1}$.*

The lemma shows that the electricity price can fall if the battery is empty and the price can rise if the battery is full. However, if the battery is neither empty nor full, then it could be used to arbitrage any price differences, and therefore the equilibrium price must be constant.

Using these lemmas, we can establish a proposition that gives intuitive formulas for the derivative of the Lagrangian with respect to installed capacity.

Proposition 1. *The derivatives can be written:*

$$d\mathcal{L}/dK_i = \sum_t \max\{p_t - c_i, 0\} f_{it} - r_i = \left(\sum_t (p_t - c_i) q_{it} - r_i K_i \right) / K_i.$$

and $d\mathcal{L}/d\bar{S} = \sum_t -p_t b_t / \bar{S} - r_s$.

The derivatives in Proposition 1 are simply profit per unit capacity, and they create a gradient, which we can use to find optimal capacities in the simulation. In addition, setting the derivatives equal to zero implies that $\sum_t (p_t - c_i) q_{it} = r_i K_i$ for each i and $\sum_t -p_t b_t = r_s \bar{S}$, *i.e.,* that optimal capacity investments result in zero profit for each technology. Zero profit is consistent with competitive entry and exit in a long-run equilibrium.

The long-run competitive equilibrium, characterized by the optimum to [9], may not be efficient because of the external costs from carbon emissions. Accordingly, we define *private surplus* as the optimized value of [9] and *welfare* as the private surplus minus the damages from pollution plus net government revenue from any tax or subsidy policy. These definitions enable us to analyze policies such as carbon taxes, technology subsidies, and electrification.

Some intuition of policy analysis from short-run models, in which capacity is fixed, also applies to the long run. For example, carbon pricing reduces carbon emissions, and renewables subsidies increase renewable generation. However, the long run features many results that do not appear in short-run models. For example, carbon taxation can *increase* electricity consumption. Under a carbon tax τ the operating cost of fossil generation is $c_i + \beta_i \tau$. Letting Δ denote the difference operator, we have

Result 1. *If carbon taxes increase, $\Delta\tau > 0$, then emissions decrease, $\Delta \sum_i \sum_t \beta_i q_{it} < 0$, but total electricity consumption can increase or decrease, i.e., $\Delta \sum_t Q_t \lesseqgtr 0$.*

Intuitively, carbon taxation increases the costs of polluting technologies. This induces these technologies to exit, which potentially increases electricity prices during hours in which they are on the margin. But these higher electricity prices can induce entry of other, cleaner technologies and drive down electricity prices in hours in which cleaner technologies are on the margin. Higher electricity prices in some hours and lower electricity prices in other hours can increase or decrease overall electricity consumption depending on the relative elasticities of demand.

Our next result relates emissions to the capital cost of renewable generation, which may be affected by subsidy policies.

Result 2. *If the capital cost of renewables decreases then carbon emissions can increase or decrease, i.e., $\Delta \sum_i \sum_t \beta_i q_{it} \lesseqgtr 0$.*

Intuition suggests that a decrease in the cost of renewables would increase renewable capacity and generation and hence reduce emissions. But emissions can increase if the renewable capacity leads to a decrease in capacity for a low operating cost, zero-emission technology (such as nuclear) and an increase in the capacity of a polluting technology.

Electricity storage can reduce price differences across hours and thereby affect the efficiency of policies. The next result shows how the equilibrium responds as storage becomes cheaper. Defining the *levelized cost* of technology i as $c_i + \frac{r_i}{\sum_t f_{it}}$, we have:[21]

Result 3. *If the capital costs of storage, r_s, decreases, renewable capacity can increase or decrease. If $r_s = 0$, then the equilibrium electricity price is the same in each period, i.e., $p_t = \bar{p}$ for all t, where $\bar{p}$ is given by*

$$\bar{p} = \min_i \{c_i + \frac{r_i}{\sum_t f_{it}}\}.$$

[21] Our definition of levelized cost assumes capacity factors, f_{it}, are exogenous. Other definitions of levelized cost assume endogenously determined capacity factors.

Moreover, if the levelized cost, $c_i + \frac{r_i}{\sum_t f_{it}}$*, is unique across technologies, then the capacity of the technology* i *that satisfies the minimum is given by* $K_i = \frac{\sum_t D_t(\bar{p})}{\sum_t f_{it}}$.

Although it may seem intuitive that battery storage may result in more renewables, Result 3 shows that this is not necessarily the case.[22] If intermittent renewables generate electricity in high-price periods, then storage will reduce their profitability. Conversely, if they do not, then storage will increase their profitability. In the limit, as the capital cost of storage goes to zero, only the technology with the lowest levelized cost is built.[23] In particular, if natural gas-fired generation has a lower levelized cost than renewables, then a low-cost storage technology will drive renewables from the equilibrium. Thus storage can help or hinder decarbonization.

Another interesting difference between the short and long run is the effect of increasing demand in some periods, such as will occur with electrification. In the short run, marginal emissions from demand increases are positive if increased electricity is supplied by a polluting source. At best, short-run marginal emissions can be zero if, for example, the increased electricity is supplied by renewables. In contrast, the following result shows that electrification can *decrease* emissions in the long run.

Result 4. *If electricity demand increases in some period(s), then carbon emissions can increase or decrease, i.e.,* $\Delta \sum_i \sum_t \beta_i q_{it} \lesseqgtr 0$.

Increasing demand in some period puts upward pressure on the price and induces entry of the marginal technology for that period. However, once additional capacity enters, it may be used in other periods. Thus if the marginal technology is dirty, carbon emissions may increase by more than the emissions rate of the marginal technology. Conversely, if the marginal technology is clean, its entry may meet the increased demand and offset emissions in other periods, thereby decreasing overall emissions. In addition to changes in the mix of generation technologies, electrification can have price effects. Prices face upward pressure in periods with demand increases but downward pressure in periods with additional capacity.

[22] Shrader et al. (2021) find a similar result in which storage is ineffective in reducing emissions.

[23] Implicitly the result assumes that the year is infinitely repeated and is in a steady state. We capture this in our simulations by starting the year in the hour at which the battery state would be at a minimum in the steady state with the lowest cost technology.

Thus, the long-run change in overall electricity usage may be greater or less than one-for-one with electrification.

The model has been designed to capture the essential features of electricity markets in an analytically tractable way. In Online Appendix Section O.A.4 we briefly discuss extensions to the model that account for other aspects of electricity markets such as ramping constraints and upward sloping supply curves for inputs to renewable generation. It is straightforward to extend the results by adapting the planner's problem to account for these complications.

3 Model calibration and solution algorithm

To quantify long-run policy effects, we calibrate our model for a representative year, 2019, based on hourly observed electricity consumption and hourly availability of generation from solar and wind for thirteen EIA electricity regions (Figure 1).[24] Using observed 2019 consumption and renewable availability provides a realistic approximation of the underlying structural correlations between electricity consumption and renewable availability both over time and over geographic locations. We initially consider each EIA region to be independent to capture geographic variation in load and renewable availability, but we later combine them to capture the benefits of increasing transmission capacity between them.

3.1 Demand calibration

Modeling hourly demand in each electricity region requires assumptions about functional forms and data on observed prices and quantities. We generally assume linear demand in each hour that is independent of demand in other hours.[25] Each hourly demand function is parameterized by the observed consumption and price and an assumed elasticity of -0.15 at the observed consumption-price pair.[26]

[24]The model could be calibrated using multiple years. We use 2019 because it is the first full year of the EIA 930 dataset and because 2020 and 2021 were abnormal due to the COVID-19 pandemic.

[25]Linear demand allows for the possibility of curtailed renewable generation. We also consider iso-elastic demand as a robustness check.

[26]This assumption on elasticity is appropriate for the planner's problem in our theoretical model in which consumers respond to price in each hour. Additional constraints would be needed if the consumers' faced regulated prices that were constant across hours.

Observed hourly electricity consumption is collected from the EIA 930 and is the total of load from all reporting entities within the EIA region for that hour. The mean observed consumption by season and hour of day is shown in Figure O.A.2 for each EIA region. Observed hourly prices come from multiple sources. For the regions that are organized into markets (California, Texas, New England, MidWest, New York, MidAtlantic, and Central), we gather data on hourly market prices for each ISO. These prices are weighted averages of real-time single bus prices or aggregated regional hub prices. For the regions not in organized markets, system lambdas from FERC 714 proxy for observed prices. The mean hourly price is shown in Figure O.A.4 and summary statistics are in Table O.A.1. The observed consumption and prices show substantial variation across hours, seasons, and regions which we assume is representative of underlying structural demand conditions.

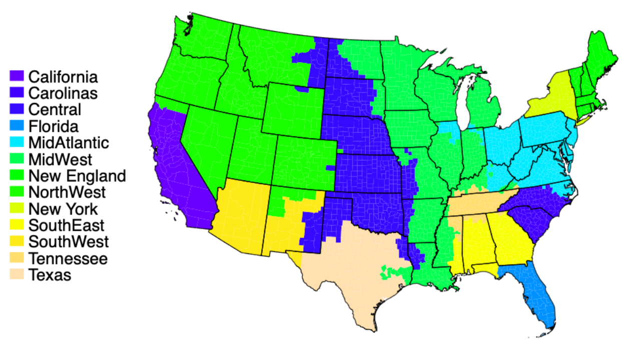


Figure 1: Map of EIA regions.

3.2 Capital and operating costs

We consider five generation technologies: solar, wind, nuclear, combined cycle gas, and combustion turbine (peaker) gas (Table 1). Peaker gas plants have low capital costs but high operating costs, and hence are used primarily when electricity prices are high. Combined cycle gas plants have higher capital costs than peakers but lower operating costs, and are used for more hours. Our other three technologies have no carbon emissions. Advanced nuclear has very low operating costs but very high capital costs. Solar and wind power both have zero operating cost and intermediate capital costs. If they were dispatchable, these technologies would dominate advanced nuclear, but because of intermittency, the equilibrium may have positive capacities of nuclear and renewables.

Table 1: Capital and Operating Costs for Different Technologies

	Overnight Cost ($/kW)	Annual Capital Cost ($/MW)	Operating Cost ($/MWh)	CO_2 Emissions (tons/MWh)
Gas Combustion Turbine	585	54,741	44.13	0.526
Gas Combined Cycle	871	79,489	26.68	0.338
Advanced Nuclear	5,852	528,307	2.38	0
Wind (onshore)	1,426	132,602	0	0
Solar PV	878	83,274	0	0
Battery Storage	205*	18,935*	0	0

Notes: Source EIA (2021) "Table 1b. Estimated unweighted levelized cost of electricity (LCOE) and levelized cost of storage (LCOS) for new resources entering service in 2026 (2020 dollars per megawatthour)". "Overnight Cost" is the levelized capital cost in Table 1b adjusted for the capacity factor and capital recovery factor assuming a 30-year cost recovery period and a weighted average cost of capital (WACC) of 5.4%. "Annual Capital Cost" is the sum of the levelized capital, fixed O&M, and transmission costs from Table 1b adjusted for the capacity factors. "Marginal Cost" is the levelized variable cost from Table 1b. Capital cost of battery storage is in MWh. All dollar amounts in the paper are in 2020 dollars.

We do not consider coal technologies. Even ignoring environmental costs, coal technologies are dominated by our combined cycle gas technology at all levels of utilization. In fact, the long run average cost of coal is double that for combined cycle gas. Section O.A.6 in the Online Appendix details how costs would have to change to make coal viable in our model.

Our baseline capital and operating costs for the five generation technologies and for grid-scale battery storage represent capacity entering service in 2026. Following EIA (2021), our annual capital cost, r_i, assumes a 30-year cost recovery period and a weighted average cost of capital of 5.4% and includes fixed operating and maintenance and transmission costs for each technology. The capital costs are forward looking and highly speculative. EIA (2021) shows that capital costs of renewables have declined dramatically from 2014 to 2021, and projections to 2050 suggest large future declines for capital costs of solar and storage. Because of the speculative nature of these distant forecasts, our baseline focuses on 2026 costs, and we consider sensitivity analysis to a wide range of assumptions.

Operating cost, c_i, is the levelized variable cost and is primarily fuel costs for the natural gas technologies. Because carbon taxes and natural gas prices both increase the operating cost of generation from gas, our carbon tax simulations can be reinterpreted as sensitivity of our results to the price of natural gas.[27]

3.3 Capacity factors for renewables

To calibrate hourly renewable capacity factors for 2019 conditions, we use hourly wind and solar generation reported in the EIA 930. Renewable capacity, which is required to calculate our capacity factors, is not reported in the EIA 930 and is increasing rapidly throughout 2019. To address this limitation, we aggregate monthly renewable generation from the EIA 923 and monthly renewable capacity from EIA 860 across all plants built after 2010 in a region which report to both datasets.[28] Dividing these gives region-month capacity factors. We then divide the mean hourly generation for each region by the region-month capacity factors to calculate region-month renewable capacity. Dividing hourly generation by the region-month capacity gives our hourly capacity factors. Figure O.A.3 shows mean hourly capacity factors by season and hour of day for each region, and summary statistics are in Table O.A.1. The capacity factors show seasonal and hourly patterns which are consistent with estimates of renewable availability.

3.4 Solution algorithms

We use two different approaches to solve the planner's problem. If the benefit function $U_t(Q_t)$ is quadratic, then the planner's problem is a quadratic program and we solve it directly using a publicly available algorithm.[29] This approach finds the solution relatively quickly, but can only be used when the benefit function is quadratic. The second approach (see Online Appendix O.A.1) uses the theoretical results to dramatically reduce the dimensionality of the choice vector and then uses a gradient search algorithm to optimize capacity for each

[27] For combined cycle gas technology, a \$10 increase in the carbon tax corresponds to a \$0.53 per MMBTU increase in natural gas prices.

[28] The EIA 930 is missing hourly solar generation for New York and hourly wind generation for Carolinas, Florida, SouthEast, and Tennessee. We use estimates of available renewable resources to construct capacity factors for these regions and technologies. See Appendix A.2 for details.

[29] The particular algorithm that we use is described in Stellato et al. (2020) and downloaded from `https://osqp.org/`. Unlike many other quadratic programming algorithms, this one allows the objective function to be positive semidefinite, a feature that is necessary for our problem.

technology.[30] This approach is slower than the quadratic programming approach, but can be applied to more general benefit functions (in particular the benefit function corresponding to iso-elastic demand).

4 Decarbonization

Decarbonization may occur through pathways such as carbon pricing, increasing transmission, or reductions in the costs of renewables, nuclear, or batteries. We analyze the potential of each of these pathways and then use welfare analysis to analyze policies promoting these pathways individually or in combination.

4.1 Carbon pricing

Our baseline calibration of the long-run equilibrium has CO_2 emissions of 1,104 million metric tons (mmt) per year (Table O.A.2), which is 30% lower than actual 2019 CO_2 emissions.[31] This difference arises because there is no modeled coal generation and because modeled electricity consumption is slightly lower than actual.[32] Thus optimally building the electricity grid using current technologies could reduce carbon emissions significantly even in the absence of carbon pricing.

Carbon pricing reduces long-run carbon emissions further (Figure 2). Relative to our baseline, a carbon tax of $50 per ton of CO_2 reduces long-run carbon emissions from the electricity sector by 50% and a $150 tax reduces emissions by 95%.[33] Consistent with Result 1, total electricity consumption can be higher or lower with a carbon tax. With linear demand, the $200 carbon tax has annual electricity consumption about 15% lower than baseline. However, with iso-elastic demand, the relationship is not monotonic: a higher carbon

[30] Borenstein (2005) presents a conceptually elegant and computationally efficient algorithm for calculating equilibrium capacity investment. Unfortunately, that algorithm requires a strict ranking of technologies in terms of capital and operating costs, and with intermittent technologies, such a ranking is meaningless.

[31] Actual 2019 CO_2 emissions were 1604 mmt (Holland et al. (2022)). With iso-elastic demand, modeled CO_2 emissions are 1,151 mmt (Table O.A.2). We use metric tons throughout.

[32] Modeled electricity generation has a lower percentage of renewable generation: 4% compared to the 2019 actual share of 9%. Our baseline does not include existing renewable subsidies and portfolio standards.

[33] The carbon tax required for deep decarbonization is higher than that calculated by Stock and Stuart (2021). This difference is likely due to the rich set of representative time periods in our model, as discussed in Online Appendix O.A.2.

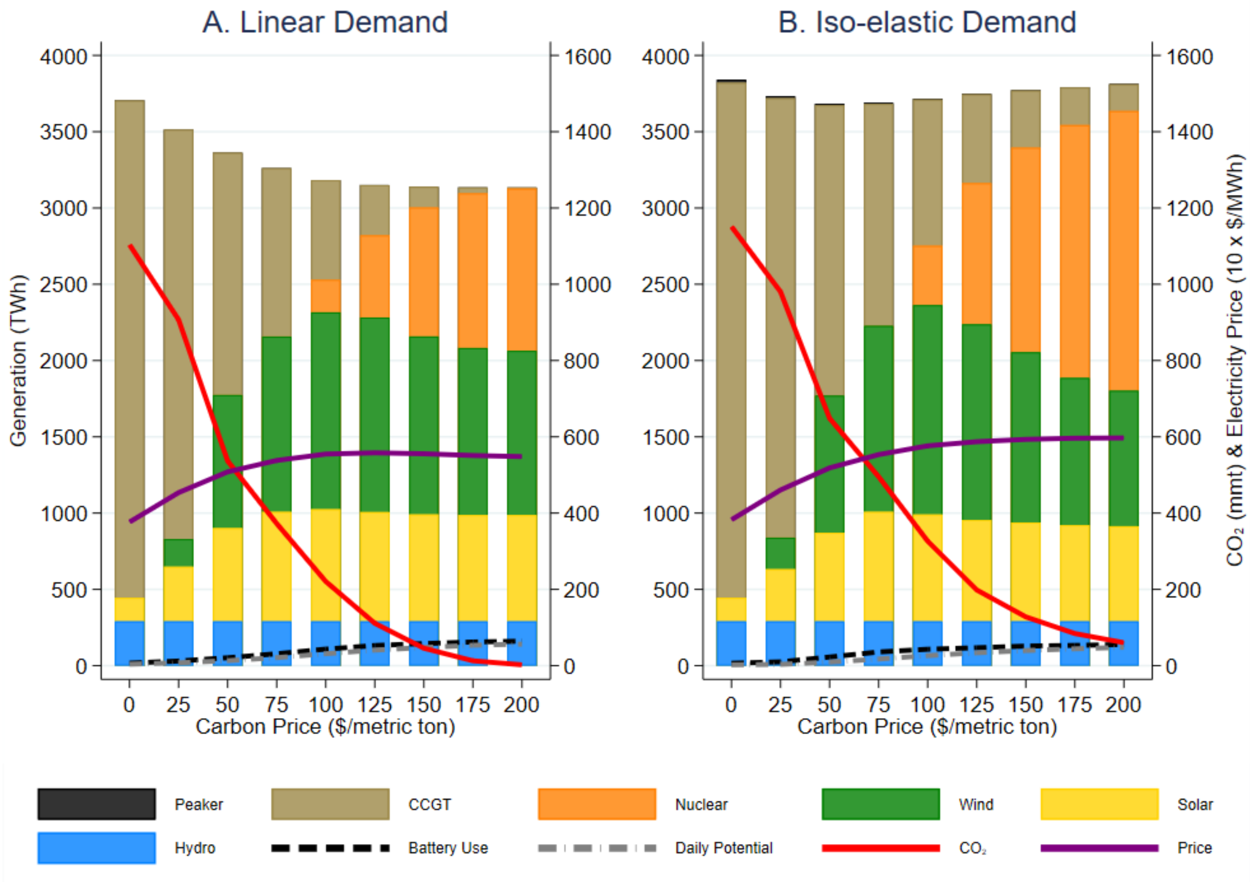


Figure 2: Carbon pricing aggregated across all regions.

Notes: Panel A has baseline parameterization and panel B has iso-elastic demand. Baseline parameterization includes linear demand, storage, no interregional transmission. Results aggregated across all regions. Battery use (TWh) is sum of charges added to battery. Daily potential (TWh) is battery use if battery is fully charged (and discharged) once a day.

tax first decreases then increases electricity consumption, and overall the $200 carbon tax only decreases electricity consumption less than 1%. This decarbonizes electricity without substantial decreases in electricity consumption. Furthermore, while electricity prices increase with carbon prices up to about $100, higher carbon prices have negligible additional effects.

Carbon pricing changes the long-run mix of generation technologies. In the baseline, natural gas accounts for 88% of total generation but is gradually eliminated at higher carbon prices. At carbon taxes above $100 per ton, installing nuclear capacity is optimal in

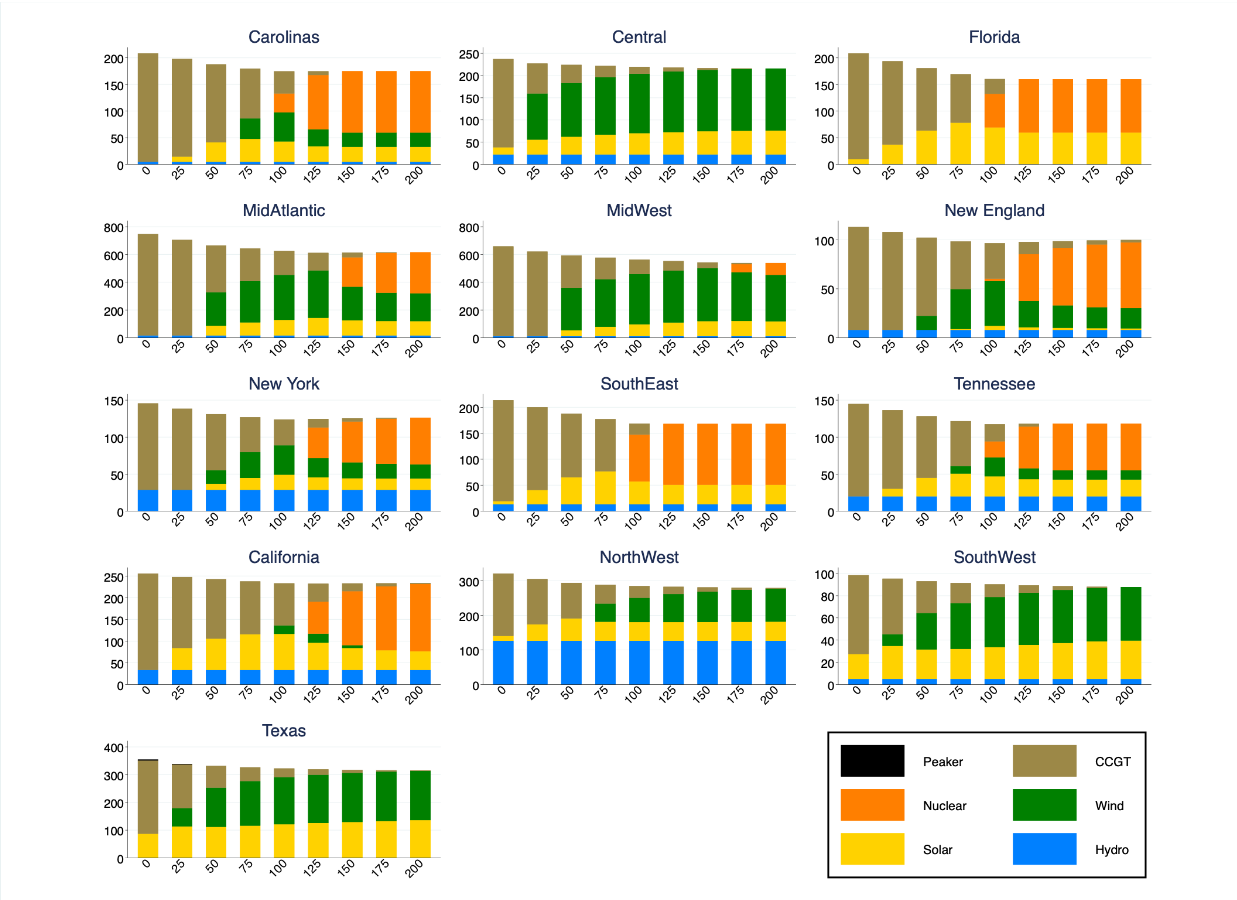


Figure 3: Carbon pricing for each region.

Notes: Baseline parameterization.

some regions. Because nuclear capacity is dispatchable and has low operating cost, nuclear capacity displaces both renewables and gas, so that renewable generation accounts for a lower share of the generation mix at carbon prices above \$100. The generation mix differs across regions primarily due to differences in renewable potential (Figure 3). The Central, Midwest, Northwest, SouthWest, and Texas regions all have good wind resources and install substantial wind capacity at high carbon prices. All other regions install substantial nuclear capacity even if solar is available because solar is intermittent. Batteries play a relatively minor role. They cycle about once per day on average, so they do not store electricity across seasons (Figure 2). In the baseline, battery use is less than 1% percent of total generation and only about 5% percent of total generation at a carbon price of \$200.

4.2 Reducing capital costs of renewables and nuclear

In the absence of carbon pricing, electricity can be decarbonized by simply building renewable or nuclear capacity. To explore the potential of these pathways, we consider reductions in capital costs. These reductions may occur due to technological advances or public policies. Either way, market participants would optimally react by increasing installation of technologies that have become cheaper.

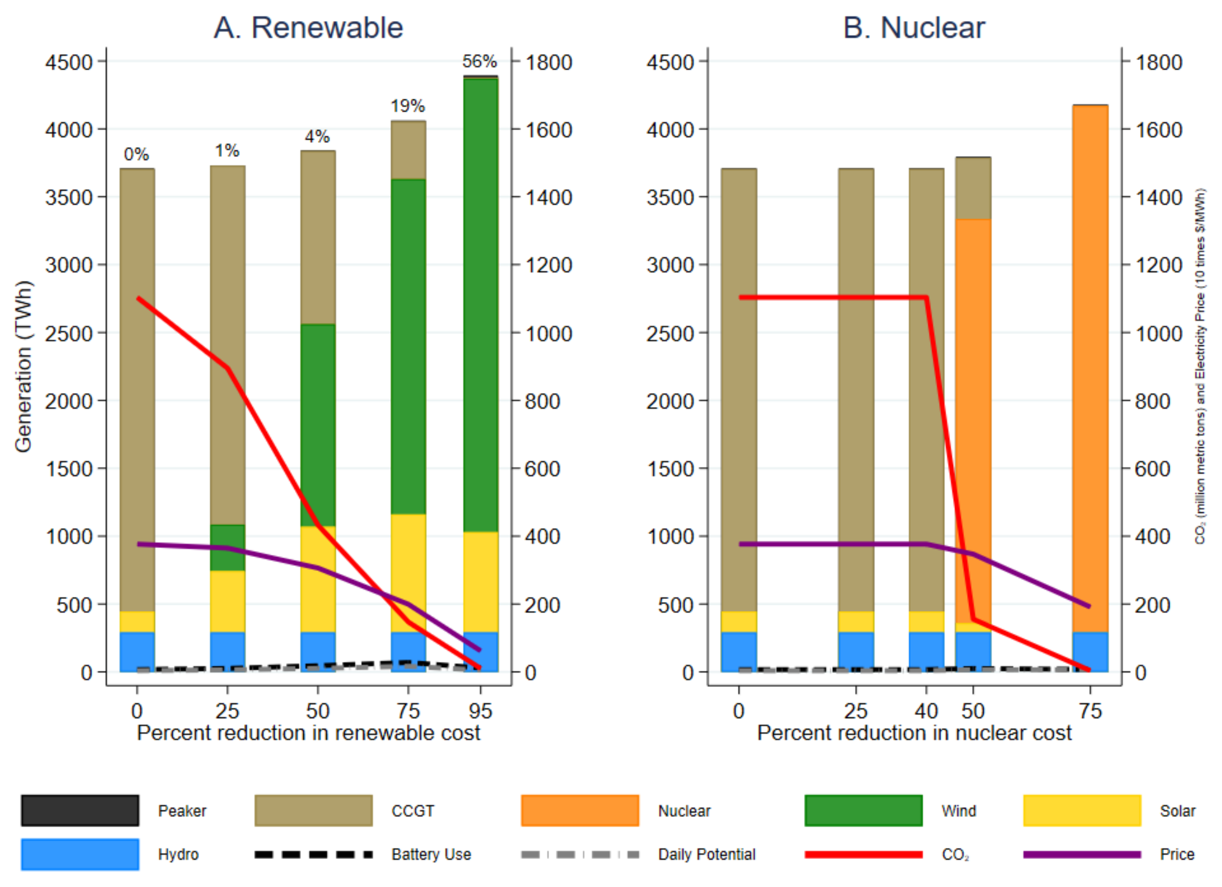


Figure 4: Reduction in renewable capital costs and reduction in nuclear capital costs.
Notes: Baseline parameterization aggregated across all regions. For renewable, generation is utilized generation, and the percentages show the percent of potential renewable generation which is curtailed (not utilized).

Result 2 shows that lower renewable costs can decrease or increase carbon emissions. Our calibration finds that lower renewable capital costs reduce carbon emissions quite dramatically (Panel A of Figure 4).[34] A 25% reduction in renewable capital costs reduces carbon emissions by 19% and a 95% reduction in costs basically eliminates carbon emissions. This reduction in emissions is primarily from the installation of wind capacity which accounts for the majority of electricity generation when renewable capacity is cheap. At a 95% cost reduction, wind generates 76% of electricity, and solar only generates 17% of electricity. With this level of renewables, gas generates less than 1% of electricity and is primarily peaker capacity for use in the few hours in which wind or solar are not available.[35]

Because renewables are not dispatchable, more renewables leads to an increase in total capacity. With a 95% renewable cost reduction, total capacity is six times higher than baseline.[36] Increases in renewable generation are not proportional to increases in capacity because renewable generation is increasingly installed in regions with lower capacity factors,[37] and because substantial renewable generation is curtailed with linear demand. If renewable capital costs are 95% below baseline, then a very large share (56%) of renewable generation is curtailed (Figure 4).[38] This dramatic curtailment is optimal only because renewable generation is very inexpensive and is profitable in enough hours to cover its capital costs.

Decarbonization can also result from installing nuclear capacity, but this pathway exhibits severe threshold effects. Panel B of Figure 4 shows nuclear capacity is zero even if nuclear capital costs fall by 40%. If, however, capital costs fall by 50%, then nuclear power becomes the dominant power source, replaces both renewables and natural gas generation, and decarbonizes electricity generation.

If renewable or nuclear costs fall due to some breakthrough technology, then society benefits because electricity prices fall, electricity consumption increases, and emissions decrease. Formally, we define benefits as the change in consumer surplus plus the reduction in damages

[34]Panel B of Table O.A.11 shows the surprising result where lower renewable costs increase emissions by crowding out zero carbon nuclear power.

[35]The generation by region is shown in Figure O.A.8.

[36]This requires 0.8 million MW of solar and 2.8 million MW of wind capacity. At a rate of 5 acres of land per MW, solar capacity would require about 4 million acres which is about five times the size of Rhode Island or about six percent of Arizona. At a rate of 40 acres per MW, wind capacity would require 112 million acres which exceeds the size of Nebraska and Kansas combined.

[37]For the 95% cost reduction, solar capacity is higher than baseline by a factor of 12, but potential solar generation is only higher by a factor of 10. Starting from a low baseline, wind capacity is higher by a factor of 231 but potential wind generation is only higher by a factor of 170.

[38]Panel B in Table O.A.3 and Figure O.A.7 show the case of iso-elastic demand in which, by assumption, no generation is curtailed.

evaluated at the SCC. Even if the SCC is zero, a 75% cost reduction in renewables results in \$58 billion annual benefits (Table O.A.3). With a positive SCC, the benefits are even greater: \$106 billion to \$249 billion per year depending on the SCC. For nuclear, a 50% reduction in capital costs creates benefits that exceed \$100 billion for values of the SCC that are greater than \$100 per metric ton of CO_2. These benefits show substantial returns to research and development spending that reduces the cost of renewables or nuclear power.

4.3 Expanding transmission and battery storage

Transmission and battery capacity can contribute to decarbonization by shifting renewable electricity from low- to high-value locations or times. The effects depend on the amount of renewable generation, so we analyze increasing transmission and batteries in our baseline and with lower renewable costs.

Our baseline assumes no electricity transmission between regions. Following Cicala (2022), we model investments in transmission by combining load and dispatchable capacity across EIA regions while retaining each region's renewable capacity to capture temporal and spatial variation in renewable availability.[39] We model five scenarios with increasing levels of interconnection between the EIA regions so that Scenario 5 assumes perfect transmission (*i.e.,* a single hourly electricity price) throughout the entire contiguous U.S. This scenario requires capacity optimization for 29 different technologies: three dispatchable technologies, 13 wind technologies, and 13 solar technologies.

Carbon emissions reductions from transmission expansion are relatively small in our baseline (Panel A of Figure 5). Full interconnection (Scenario 5) results in additional solar and wind generation but only reduces carbon emissions 15% from baseline. With lower cost renewables, additional transmission decreases carbon emissions substantially (Panel B of Figure 5). Interconnecting the East (Scenario 3) decreases carbon emissions by 57%, and full interconnection (Scenario 5) decreases carbon emissions by 67% relative to Scenario 1.[40] As with reductions in capital costs, we can calculate the benefits of increasing transmission

[39] Essentially, this assumes sufficient transmission between regions that there are no locational differences in prices, and hence no returns to owners of transmission capacity. This level of transmission capacity would not be constructed by competitive markets unless transmission capacity were costless.

[40] Figure O.A.10 show the first-best transmission capacity expansion for an SCC of \$100.

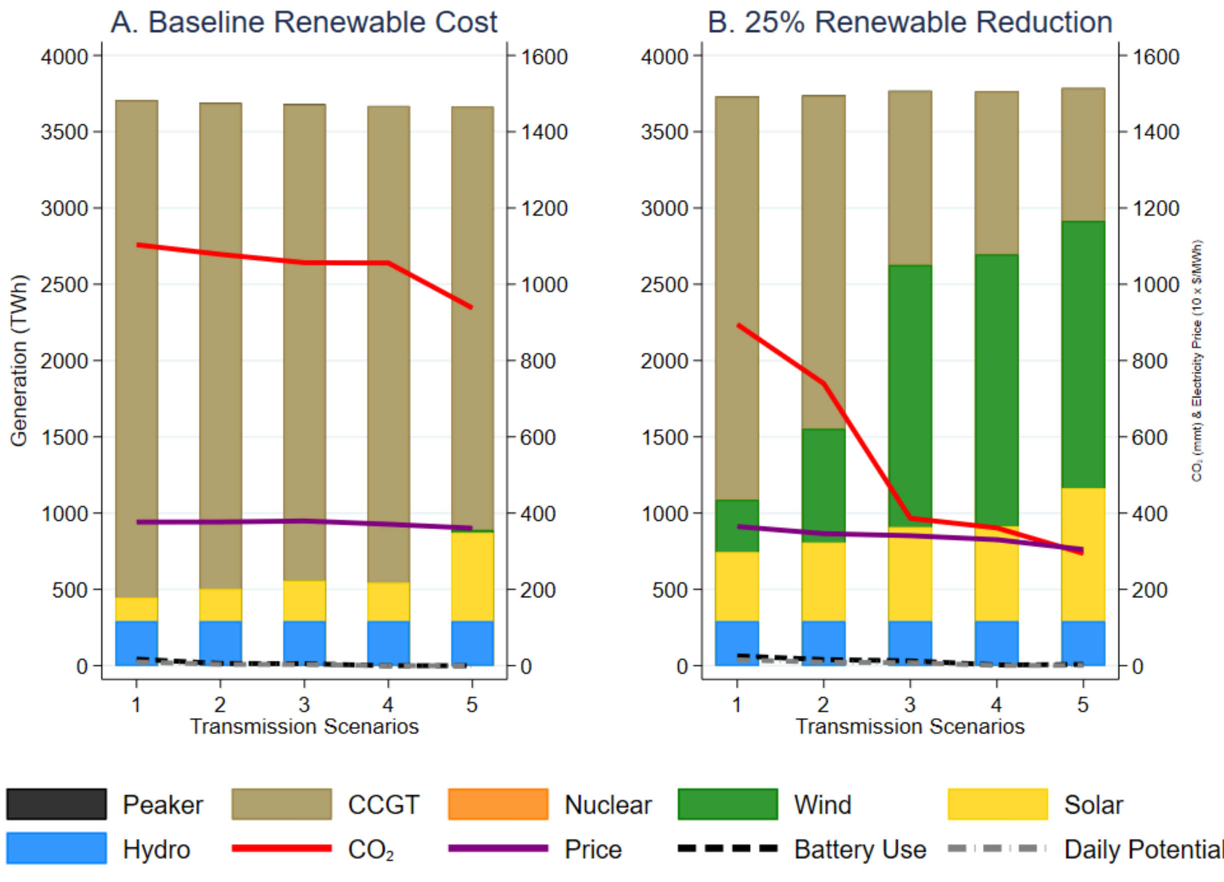


Figure 5: Scenarios increasing transmission.

Notes: Baseline parameterization. The Baseline (Scenario 1) has 13 distinct transmission regions. Scenario 2 has 5 distinct transmission regions: NE, SE, MW, Texas, and West. Scenario 3 has 3 distinct transmission regions: East, Texas, and West. Scenario 4 has 2 distinct transmission regions: East plus Texas, and West. Scenario 5 has 1 unified transmission region for the whole country.

capacity. Assuming the SCC is \$100, annual benefits of full interconnection are \$24 billion in our baseline, but exceed \$100 billion if renewable costs are lower (Table O.A.5). For policy analysis, these benefits would need to be compared with the costs of transmission capacity expansion, which we do not model. In summary, transmission expansion can contribute to substantial decarbonization, but only with a coincidental decrease in renewable capital costs.

Moving electricity from low- to high-value times requires electricity storage. Batteries play a relatively minor role in the decarbonization pathways discussed above, even though our baseline calibration reflects the recent decreases in battery costs. Result 3 gives a theoretical explanation for this, and indeed we find lower battery costs increase carbon emissions

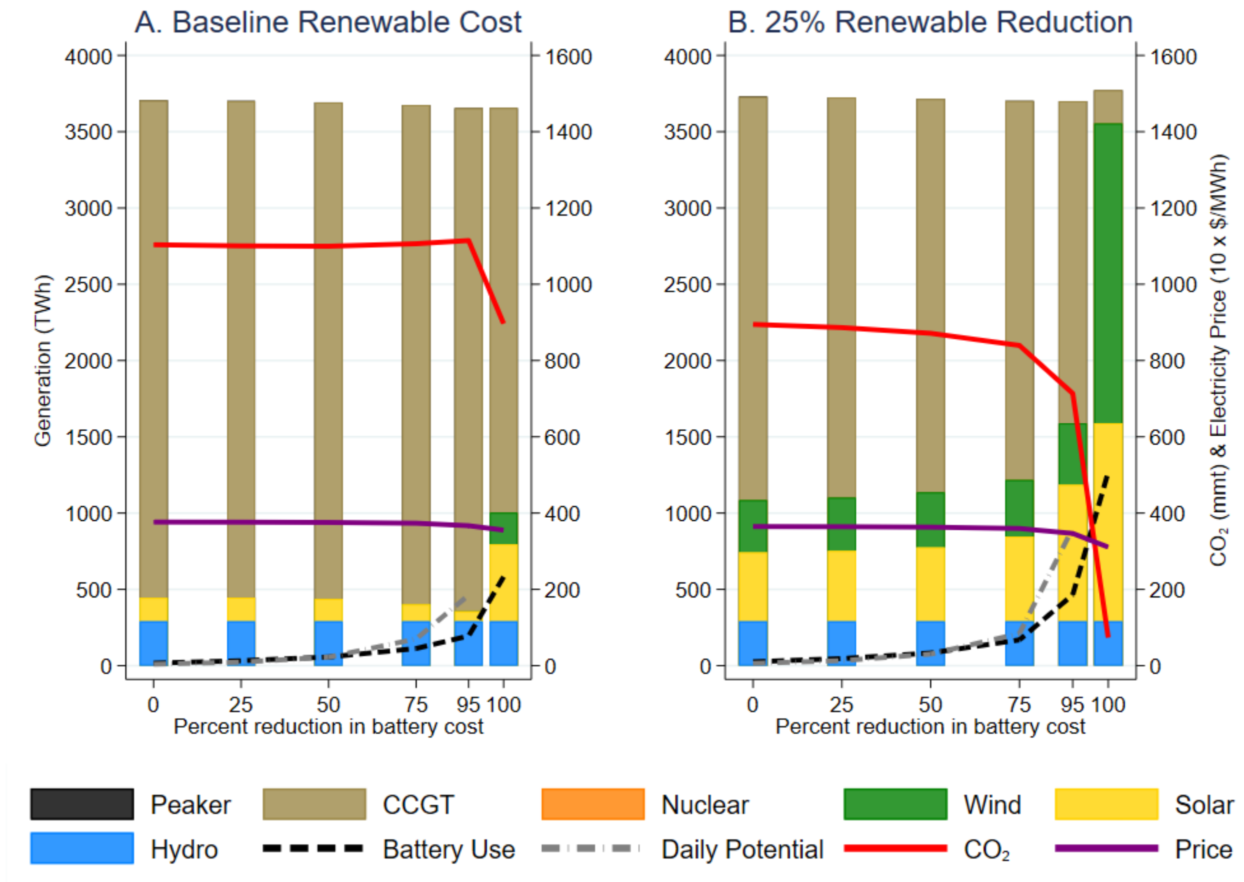


Figure 6: Reduction in battery capital costs.
Baseline parameterization aggregated across all regions.

modestly for some parameters.[41] Nevertheless, the effects may be different with dramatic drops in battery costs. Figure 6 shows the effects of lower battery costs both for our baseline and for reduced renewable costs. Carbon emissions are essentially flat unless battery costs fall by more than 95%. In this case, batteries are used for interseasonal storage (battery usage is less than daily potential), battery capacities become enormous, and generation is increasingly from the technology with lowest levelized cost. In the limit, if battery costs fall 100%, i.e. are costless, Result 3 shows that only the technology with the lowest levelized cost would be constructed. These levelized costs and required capacities are shown in Table O.A.7. In our baseline, the lowest levelized cost technology is gas in nine out of thirteen regions. Overall our calculations show the decarbonization potential for batteries are modest

[41]Figure O.A.12 shows that SouthEast and Texas increase natural gas generation as batteries become cheaper in our baseline, but not if renewables are cheaper, as shown in Figure O.A.13. Panel A of Table O.A.6 shows this at the national level.

unless technological innovation can make batteries essentially free and renewable costs are lower than baseline.

4.4 Policies and policy interactions

We have described the benefits of pathways that lead to decarbonization. Here we consider the comprehensive welfare effects, which account for these benefits as well as any policy costs or benefits (*e.g.,* renewable subsidy expenditures or carbon tax revenue). This framework allows welfare analysis of policies supporting different decarbonization pathways either singly or in combination.

In our model, a Pigouvian carbon tax attains the first best and the annual welfare gains can be substantial (Panel A of Table 2). If the SCC is $100, then the tax leads to $48 billion in annual welfare gains.[42] To put this number in perspective, it is approximately 33% of the total revenue from electricity generation in our baseline. In practice, such a policy is unlikely to be implemented due to a variety of political, institutional, equity, and informational constraints.

Other policies generally are not efficient. To assess the magnitude of the inefficiencies, Panel B of Table 2 shows the second-best subsidy level (as a percent of capital costs) for each technology and the relative welfare gains for different SCCs.[43] So for example, if the SCC is $50, then the welfare maximizing renewable capital cost subsidy is 34 percent and this leads to $8.5 billion welfare gains relative to baseline of no policy. Across all the policies, optimal subsidies are higher for higher SCCs. Subsidies for wind are better than subsidies for solar, and since the optimal wind and solar subsidies are quite similar percentages, subsidizing renewables (wind and solar at the same rate) is much better than the individual subsidies. Nuclear subsidies can be effective at high SCCs. At low SCCs, renewable subsidies have the highest welfare gains, but at an SCC of $250, the optimal nuclear subsidy of 59% has the highest welfare gains. As one might expect from our previous discussion of batteries, the optimal battery subsidies are small and result in only modest welfare gains. Comparing

[42]Because the SCC is highly uncertain, Table O.A.2 presents the annual welfare gains for a wide range of SCCs ranging from $0 to $200 per metric ton of CO_2.

[43]More detail on the results presented in Table 2 are presented in Tables O.A.6 through O.A.11.

Panel B to Panel A shows that an effective second-best policy can capture about 70-80% of the first-best welfare gains.

Policies supporting batteries may be better in combination with other policies. Panel C of Table 2 shows the increment/decrement to the second-best subsidy levels and the relative welfare gains for different policy combinations. Optimal battery subsidies are generally larger in combination with other subsidies.[44] The biggest gain from battery subsidies is in combination with solar subsidies. However, the battery and solar combination yields a welfare gain which is less than the gain of subsidizing renewables alone. For example, with a SCC of $150, battery and solar subsidies give a welfare benefit that is $2 billion greater than the optimal solar subsidy, but this is less than the $73 billion attained by the renewable subsidy on solar and wind. Overall the additional battery subsidies only tend to reduce the optimal single subsidy modestly and do not change the overall ranking that renewable subsidies are better for low SCCs but nuclear subsidies are better for high SCCs.

5 Electrification Results

A decarbonized economy likely requires both a decarbonized electricity sector and electrification of other sectors. By increasing electricity demand, electrification may increase prices in some hours and induce capacity expansion in the long run. The additional capacity may directly affect emissions and can potentially lower prices and increase electricity consumption in other hours. To analyze these complex interactions, we first model small load shocks and then model large scale electric vehicle (EV) adoption.

[44]The only exception is for combinations with wind subsidies at low SCCs.

Table 2: Welfare gains of Pigouvian taxes and second-best subsidies

Policy	Annual Welfare Gains ($ billions) for SCC of $50	$100	$150	$200	$250
Panel A: First best					
Pigouvian Carbon Tax	11.91	48.12	97.56	151.89	207.03
Panel B: Second-best subsidy					
Renewable	8.55	36.95	72.54	112.30	155.07
	[34]	[48]	[58]	[63]	[68]
Solar	4.01	17.65	35.57	55.19	75.86
	[35]	[53]	[62]	[69]	[73]
Wind	5.12	26.65	55.75	89.45	126.14
	[34]	[49]	[58]	[63]	[67]
Nuclear	0.00	14.87	61.12	111.45	163.31
	[0]	[46]	[52]	[56]	[59]
Battery	0.06	0.20	0.38	0.56	0.76
	[19]	[27]	[31]	[35]	[35]
Panel C: Relative gains of second-best subsidy combination					
Battery and Renewable	0.08	0.58	1.74	4.06	7.21
	[-0,-0]	[+8,-0]	[+17,-1]	[+24,-1]	[+28,-1]
Battery and Solar	0.06	0.47	2.18	8.25	21.58
	[-2,-0]	[+6,-1]	[+18,-2]	[+27,-3]	[+35,-5]
Battery and Wind	0.07	0.16	0.30	1.18	3.13
	[-2,+0]	[-7,-0]	[-8,-0]	[+15,-0]	[+23,+1]
Battery and Nuclear	0.00	0.59	1.30	1.54	2.56
	[-0,+0]	[+11,-0]	[+10,-1]	[+8,-1]	[+24,-0]

Notes: Welfare gains are relative to baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the SCC minus any subsidy cost plus revenue from any carbon tax. Panel B shows welfare of the second-best single policy. Numbers in brackets are the second-best policy values in percentage cost reduction. Panel C shows the maximum welfare gain from the two complementary policies relative to the best that can be attained by either policy in isolation. Numbers in brackets are the change in the optimal second-best subsidies relative to the values in Panel B in the order the policies are presented in Column 1.

Electrification has different temporal and locational effects. For each region and hour of the day, we consider a one percent electricity load shock, which is simply a parallel shift in that hour's demand every day. The long-run marginal emissions (LMREs) shown in Figure 7 are the difference in the total emissions in the two long run equilibria with and without the

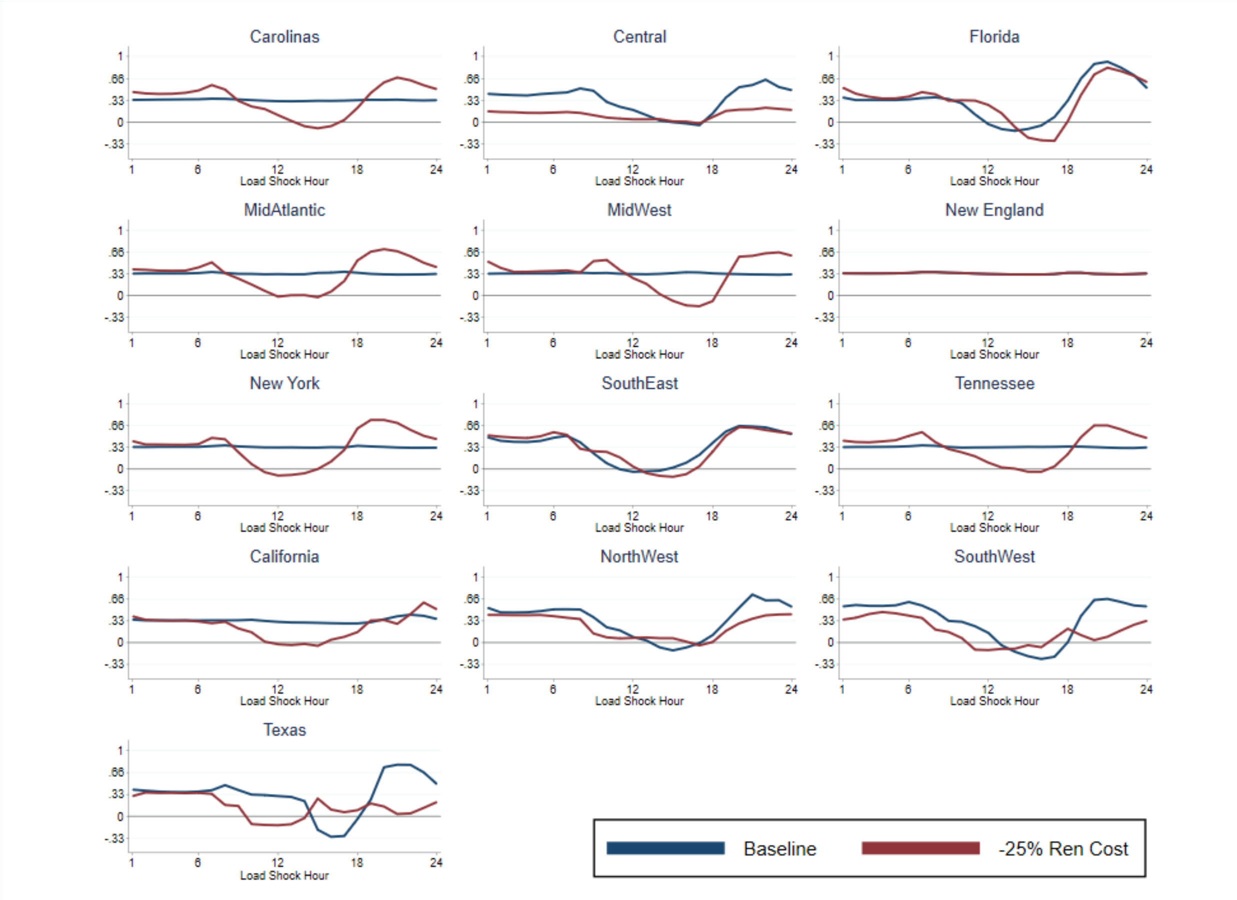


Figure 7: Long-run marginal emissions by hour-of-day for each region.
Notes: Baseline parameterization. Scenarios baseline and 25% reduction in renewable capital costs. Vertical axis is the change in emissions (mt/MWh) across all hours from a one percent shock to load in only hour h each day of the year.

shock.[45] In the baseline, there are seven regions for which a load shock in any hour of the day simply leads to an increase in the generation of combined-cycle natural gas and hence emissions increase at the emissions rate of this technology (about 0.34 mt per MWh).[46] In the other regions, the long-run effects depend on the hour of the load shock, and the temporal patterns are similar across regions. A load shock during the day leads to an increase in solar generation. The increase in solar generation may more than offset the load shock, decrease natural gas generation, and lead to negative LRMEs. Load shocks in other hours of the day

[45]Incremental generation by technology is shown in Figures O.A.14 and O.A.15.
[46]The seven regions are Carolinas, MidAtlantic, MidWest, New England, New York, Tennessee, and California.

tend to increase gas generation and, if this also decreases solar generation, then LRMEs may exceed the natural gas emissions rate by a factor of two or more.

A reduction in renewable capital costs can increase or decrease LRMEs. In midday hours, LMREs become zero or negative in all regions except New England. In regions with substantial wind availability, the LRMEs may become zero or negative in many more hours of the day: the LRMEs become very low any hour in Central; and cheaper renewables in Texas shift the hours when LRMEs are negative or zero from mid-afternoon to late morning due to higher wind generation (Figure O.A.15). In regions where lower costs induce renewable entry, LRMEs increase after sunset. These LRMEs, which are available on request, illustrate the locational and temporal differences in the effects of electrification and how they depend on decarbonization policies.

Large-scale electrification, such as EV adoption, requires increases in electricity usage across multiple hours and substantial increases in load. To analyze this, we calculate the annual EV electricity demand by first assuming electricity use of 0.25 kWh per mile at 68 degrees Fahrenheit and adjusting for locational differences in temperature to give a county-level electricity consumption rate per mile. We then multiply by the county-level vehicle miles traveled (VMT) and aggregate up to the EIA region.[47] Annual EV electricity demand for each region is then spread across hours assuming a charging profile. We first consider a 'Convenience' charging profile which assumes EVs are charged primarily at night and a 'Carbon Minimizing' profile which charges primarily in the afternoon.[48]

Panel A of Table 3 shows the effects of 50% or 100% EV adoption at baseline. For the Convenience charging profile, using EVs for 100% of light-duty VMT increases carbon emissions from electricity by 255 mmt annually but would entirely eliminate 814 mmt of carbon emissions from gasoline-powered vehicles. If we normalize by the EV electricity demand, the additional emissions, generation, and renewable generation show that the additional emissions are approximately that of natural gas, and that EV adoption does not crowd out other electricity uses but does *reduce* long-run renewable generation. For the Carbon Minimizing

[47]We use miles traveled from the US EPA Moves model for year 2011 light duty vehicles.

[48]The Convenience profile is the "EPRI profile" in Holland et al. (2016). The Carbon Minimizing profile, which is loosely based on the incremental emissions in Figure 7, has 20% of the charging in hours 12, 13, and 14, and has 40% of the charging in hour 15.

Table 3: Effects of electric vehicle adoption

Charging Profile	EV Share	Electricity Price ($/MWh)	Add'l EV CO_2 (mmt)	Avoided Gasoline CO_2 (mmt)	Add'l Emissions (mt / MWh)	Add'l Generation (MWh / MWh)	Add'l Renewable (MWh / MWh)
Panel A: Baseline renewable capital costs							
Convenience	50%	37.55	131	407	0.38	0.99	-0.13
	100%	37.08	255	814	0.37	0.99	-0.11
Carbon Min	50%	36.47	34	407	0.10	0.95	0.66
	100%	34.99	61	814	0.09	0.97	0.70
Panel B: 25% reduction in renewable capital costs							
Convenience	50%	36.37	130	407	0.38	0.98	-0.13
	100%	35.96	246	814	0.36	0.98	-0.08
Carbon Min	50%	35.58	-34	407	-0.10	0.97	1.26
	100%	33.82	-94	814	-0.14	0.99	1.39

Notes: Baseline parameterization. "Add'l EV CO_2" is the increase in electricity sector CO_2 with EV charging. "Avoided Gasoline CO_2" is the CO_2 from gasoline vehicles that are replaced by EVs. "Add'l emissions" is the increase in emissions relative to the change in EV demand; "Add'l generation" is the increase in generation relative to the change in EV demand; and "Add'l renewable" is the increase in generation from wind plus solar relative to the change in EV demand.

profile, 100% EV adoption only increases electricity sector emissions by 61 mmt. This profile has smaller additional emissions because it increases long-run renewable generation: each MWh of EV demand induces 0.7 MWh of renewable generation.

If renewable capital costs are 25% lower (Panel B of Table 3), the difference between the profiles is even starker. As before the Convenience profile has additional emissions approximately that of natural gas and reduces renewable generation. However, the Carbon Minimizing profile adds about 1.3 MWh of renewable generation for each MWh of EV charging which leads to *negative* additional emissions, without crowding out other electricity consumption. This striking result shows that it is possible to completely electrify vehicle transportation while also reducing electricity-sector carbon emissions.[49]

Although negative emissions are a tantalizing prospect, this may not be optimal when considering the overall welfare gains from EV adoption. To calculate these gains, we consider

[49]Gagnon and Cole (2022) and Powell et al. (2022) also find that charging during the day can reduce carbon emissions.

Table 4: Welfare gains of 100% electric vehicle adoption

Charging Profile	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Welfare Gains ($ billions) for SCC of $0	$50	$100	$150	$200
Panel A: Baseline renewable capital costs							
Convenience	37.08	1,359	68.2	96.1	124.1	152.0	180.0
Carbon Minimizing	34.99	1,165	52.6	90.3	127.9	165.5	203.2
Flat	37.65	1,336	68.5	97.6	126.7	155.7	184.8
Solar Profile	37.00	1,250	64.4	97.8	131.1	164.5	197.9
Wind Profile	37.64	1,340	68.4	97.3	126.2	155.0	183.9
Private Profile	37.30	1,338	71.1	100.1	129.1	158.1	187.0
Social Profile	36.68	1,233	65.9	100.2	134.4	168.6	202.8
Panel B: 25% reduction in renewable capital costs							
Convenience	35.96	1,140	60.2	88.6	117.1	145.5	173.9
Carbon Minimizing	33.82	801	41.6	87.1	132.5	177.9	223.3
Flat	36.49	1,095	60.1	90.8	121.5	152.2	182.9
Solar Profile	35.99	954	54.9	92.6	130.4	168.1	205.8
Wind Profile	36.48	1,102	60.1	90.4	120.7	151.1	181.4
Private Profile	36.05	1,056	62.2	94.8	127.5	160.1	192.7
Social Profile	35.52	923	54.7	94.0	133.3	172.6	212.0

Notes: Baseline parameterization. Annual welfare gains are for 100% EV adoption relative to zero EV adoption. The "Flat" profile has equal charging in all hours; the "Solar Profile" has charging proportional to the average solar capacity factor for that hour in that region; the "Wind Profile" has charging proportional to the average wind capacity factor for that hour in that region; the "Private Profile" charges EVs to maximize welfare assuming no carbon damages; and the "Social Profile" charges EVs to maximize welfare assuming the SCC is $100.

factors from both the electricity sector (consumer surplus, generation costs, capital costs, and externalities from the electricity generation) and the transportation sector (consumer surplus, operating costs, capital costs, and externalities from driving gasoline vehicles). We compare the welfare of an initial long-run equilibrium in which there are no electric vehicles to a new long-run equilibrium in which all gasoline vehicles are replaced with electric vehicles and the electricity sector accounts for the demand from electric vehicles.[50] In baseline without EVs, total carbon emissions are 1918 mmt, comprised of 1104 mmt from electricity generation and 814 mmt from gasoline vehicles. Table 4 shows carbon emissions and the welfare gains

[50]The calculation of welfare gains is described in detail in Appendix A.3. We do not account for the cost to consumers of charging vehicles at inconvenient times and assume the vehicles are perfect substitutes.

from EV adoption for seven charging profiles. With EVs, total carbon emissions range from 1165 to 1359 mmt. Turning to welfare, if the SCC is zero, then welfare gains are essentially equal to the favorable trade-off between the higher purchase cost and lower operating costs of EVs. In this case, the Private Profile is optimal, charging occurs primarily at night (Figure O.A.16), welfare gains are $71 billion, and total carbon emissions are 1,338 mmt. If the SCC is $100 per ton, the Social Profile is optimal. This profile charges primarily during the day (see Figure O.A.16), has welfare gains of $134 billion, and results in carbon emissions of 1,233 mmt. The Social Profile does not reduce carbon emissions as aggressively as charging under the Carbon Minimizing profile would because it accounts for the effects on consumer's surplus and the cost of generation. With lower renewable capital costs (Panel B of Table 4), the welfare rankings are similar and carbon emissions are reduced further.

These differences across charging profiles illustrate the importance of electrification timing for long-run decarbonizaton. The hours when electricity is used can be affected by pricing policies (*e.g.,* time-of-use pricing) and infrastructure construction (*e.g.,* the locations of charging stations). Our results show that policies and infrastructure that encourage EV charging during the daytime can contribute to decarbonization goals.

6 Conclusion

Decarbonization will require completely transforming the electricity grid, and our long-run model can provide guidance to the end goal of policy for the electricity sector. By ignoring legacy investments and transition costs, we can construct a simple and transparent framework for understanding the long-run effects of carbon policy in the electricity sector and of electrification. By capturing crucial aspects of the electricity industry such as time-varying demand, renewable intermittency, costly storage, and generation capacity, this framework can provide novel and realistic policy assessments.

Our theoretical model demonstrates that several surprising long-run effects are feasible with regards to carbon taxes, storage, and electrification. For example, a carbon tax could increase electricity consumption. This would require that time periods when load is saturated with renewable generation to become much more price sensitive: several companies, like

WattTime, are now providing data when renewables are likely marginal. If this leads to greater consumption during these times, then this theoretical possibility could materialize. Second, we note that cheaper storage could decrease renewable capacity investment. Unless renewables become notably cheaper than combined cycle gas turbines, our calibrated model shows that renewables would be driven out of the market in most parts of the U.S. if batteries are very inexpensive. Finally, we note that expected electricity demand growth (for example, due to greater EV penetration) could potentially decrease total emissions in the electricity sector. Using our calibrated model, we show that this is feasible if the EV charging is done in the daytime. Large adoption of charging stations in shopping centers and workplaces may facilitate this. However, current charging patterns are mostly in the evening, and this charging pattern leads to greater use of fossil fuels and a crowding out of renewables.

Beyond testing these theoretical predictions, our calibrated model provides quantitative predictions regarding key climate policies. We demonstrate that high carbon prices would lead to a national portfolio mix of nuclear, wind, and solar, albeit with notable heterogeneity across regions. Renewable subsidies outperform nuclear subsidies for modest decarbonization goals, but the ranking is reversed for ambitious goals. Transmission expansion reduces emissions only if paired with renewables polices. In particular, linking Midwest wind and Southwest solar to load centers has large environmental benefits. Batteries may be complements with renewables if both are subsidized. Note that this is consistent with current policy that allows the Investment Tax Credit (ITC) to apply to batteries that are co-located with solar investment (which also uses the ITC).

Our results show the surprising conclusion that the benefits of batteries are modest unless technological innovation dramatically decreases their capital costs. This is perhaps at odds with the intuition that batteries are required to integrate renewable generation into the grid. Some of features of the model, in particular the assumption that there is a non-zero demand elasticity and the fact that our observed renewable capacity factors may not accurately characterize the full distribution, may suggest that our results understate the benefits for batteries. But other features of the model may suggest our results overstate the benefits of batteries. We have assumed that there are no losses charging the battery, there are no losses storing energy in the battery across periods, the battery can be fully charged or discharged in a single time period, and battery operation is done with perfect foresight. Evaluating these assumptions further will take additional study, but it is not obvious that one would dominate the other.[51]

Although it is known that the environmental effects of electric vehicle adoption depend on the timing of charging (Holland et al. (2022)), our results, taken in conjunction with this previous literature, show that these effects also depend on the time horizon of the analysis. In the short run, the emissions-minimizing time to charge is when renewables are curtailed or when coal is less likely to be on the margin. In the long run, charging only during times with high renewable capacity factors induces entry and may result in negative emissions from the grid. Accounting for the tension between the long run and short run in a unified model of the transition to electric vehicles would be an interesting direction for future research.

Our modeling framework has several important caveats. Many of our parameter calibrations are highly uncertain, so sensitivity analysis is crucial. We use a small but non-zero price elasticity which assumes that prices clear electricity markets. In extreme circumstances, non-price rationing occurs in electricity markets, and this might be an additional benefit from storage which is not accounted for in our model. We assume no market power in the long run although electricity market participants often have some pricing power. Similarly, we ignore learning by doing, scale economies, and additional market failures such as learning spillovers and information asymmetries. Additionally, legacy technologies and transition costs may play a role in the feasibility of grid investments. More detailed demand calibrations and modeling of transmission congestion are important possible extensions of our work. Finally, actual solar and wind generation data for several missing regions would allow better capacity factor estimates. Given these caveats, our theoretical and calibration results provide important insights into the interactions between decarbonization and electrification policies in the long run.

[51] See Section O.A.3 for a preliminary analysis of the effect of demand elasticity.

References

Ambec, Stefan, and Claude Crampes. (2019) "Decarbonizing electricity generation with intermittent sources of energy," *Journal of the Association of Environmental and Resource Economists*, 6: 919-948.

Ambec, Stefan, and Claude Crampes. (2021) "Real-time electricity pricing to balance green energy intermittency," *Energy Economics*, 94: 105074.

Andres-Cerezo, David, and Natalia Fabra. (2022) "Storing power: Market structure matters," *Rand Journal of Economics*, forthcoming.

Borenstein, Severin. (2005) "The Long-Run Efficiency of Real-Time Electricity Pricing," *The Energy Journal*, 26(3): 93-116.

Borenstein, Severin and Stephen P. Holland. (2005) "On the Efficiency of Competitive Electricity Markets With Time-Invariant Retail Prices," *The RAND Journal of Economics*, 36(3): 469-493.

Borenstein, Severin and Ryan Kellogg. (2022) "Carbon Pricing, Clean Energy Standards, and Clean Electricity Subsidies on the Path to Zero Emissions,", Working paper.

Boomhower, Judson, and Lucas Davis. (2020) "Do Energy Efficiency Investments Deliver at the Right Time?" *American Economic Journal: Applied Economics*, 12(1): 115-39.

Brown, Patrick R. and Audun Botterud. (2021) "The Value of Inter-Regional Coordination and Transmission in Decarbonizing the US Electricity System," *Joule*, 5(1): 115-134.

Butters, Andrew R., Jackson Dorsey, and Gautam Gowrisankaran. (2021) "Soaking up the sun: Battery investment, renewable energy, and market equilibrium," NBER working paper 29133.

Callaway, Duncan S., Meredith Fowlie, and Gavin McCormick. (2018) "Location, Location, Location: The Variable Value of Renewable Energy and Demand-Side Efficiency Resources," *Journal of the Association of Environmental and Resource Economists*, 5:1, 39-75.

Cicala, Steve. (2022) "Imperfect Markets Versus Imperfect Regulation in U.S. Electricity Generation," *American Economic Review*, 112 (2): 409-441.

Davis, Lucas and Catherine Hausman. (2016) "Market Impacts of a Nuclear Power Plant Closure," *American Economic Journal: Applied Economics*, 8(2):92-122 http://dx.doi.org/10.1257/app.20140473

Davis, Rebecca, J. Scott Holladay, and Charles Sims. (2021) "Coal-fired power plant retirements in the U.S.," NBER working paper 28949.

Eisenack, Klaus, and Mathias Mier. (2019) "Peak-load pricing with different types of dispatchability," *Journal of Regulatory Economics*, 56: 105-124.

Elliott, Jonathan T. (2021) "Investment, Emissions, and Reliability in Electricity Markets," mimeo. `https://jonathantelliott.com/files/elliott_jmp.pdf`

Fell, H. and D. Kaffine. (2018) "The Fall of Coal: Joint Impacts of Fuel Prices and Renewables on Generation and Emissions," *American Economic Journal: Economic Policy*, 10: 90-116.

Fell, Harrison, Daniel Kaffine, and Kevin Novan. (2021) "Emissions, Transmission, and the Environmental Value of Renewable Energy," *American Economic Journal: Economic Policy*, 13(2): 241-272.

Gagnon, Pieter, and Wesley Cole. (2022) "Planning for the evolution of the electric grid with a long-run marginal emission rate," *i*Science, 25: 103915.

Gambardella, C., M. Pahle, & WP. Schill. (2020) "Do Benefits from Dynamic Tariffing Rise? Welfare Effects of Real-Time Retail Pricing Under Carbon Taxation and Variable Renewable Electricity Supply," *Environ Resource Econ*, 75: 183-213.

Gillingham, Kenneth, Marten Ovaere, and Stephanie M. Weber. (2021) "Carbon policy and the emission implications of electric vehicles," NBER working paper 28620.

Gowrisankaran, Gautam, Stanley S. Reynolds, and Mario Samano. (2016) "Intermittency and the Value of Renewable Energy," *Journal of Political Economy*, 124(4): 1187-1234

Graff Zivin, J., M. Kotchen, and E. Mansur. (2014) "Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies," *Journal of Economic Behavior & Organization*, 107: 248-268.

Hasanbeigi, Ali, Lynn A. Kirshbaum, Blaine Collison, and David Gardiner. (2021) "Electrifying U.S. Industry: A Technology and Process-Based Approach to Decarbonization," *Renewable Thermal Collaborative*.

Hawkes, A.D. (2014) "Long-run marginal CO_2 emission factors in national electricity systems," *Applied Energy*, 125: 197-205.

Helm, Carsten, and Mathias Mier. (2019), "On the efficient market diffusion of intermittent renewable energies," *Energy Economics*, 80: 812-830.

Heutel, Garth. (2011), "Plant vintages, grandfathering, and environmental policy," *Journal of Environmental Economics and Management*, 61: 36-51.

Holland, Stephen, Matthew Kotchen, Erin Mansur, and Andrew Yates. (2022) "Why Are Marginal CO_2 Emissions Not Decreasing for U.S. Electricity? Estimates and Implications for Climate Policy," forthcoming in *Proceedings of the National Academy of Sciences*.

Holland, Stephen and Erin Mansur. (2008) "Is Real-Time Pricing Green? The Environmental Impacts of Electricity Demand Variance," *Review of Economics and Statistics*, 90(3): 550-561.

Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates. (2016) "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," *American Economic Review*, 106(12): 3700-3729.

Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates. (2020) "Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation," *American Economic Journal: Economic Policy*, 12(4):244-74.

Holland, Stephen, Erin Mansur, and Andrew Yates. (2021) "The electric vehicle transition and the economics of banning gasoline vehicles," *American Economic Journal: Economic Policy*, 13: 316-344.

IEA (2019), "Frontier electric technologies in industry," IEA, Paris https://www.iea.org/commentaries/frontier-electric-technologies-in-industry

Imelda, Matthias Fripp, and Michael J. Roberts. (2018) "Variable pricing and the cost of renewable energy," NBER working paper 24712.

Jenkins, J.D., Z. Zhou, R. Ponciroli, R.B. Vilim, F. Ganda, F. de Sisternes, and A. Botterud. (2018) "The benefits of nuclear flexibility in power system operations with renewable energy," *Applied Energy*, 222: 872-884.

Junge, Cristian, Cathy Wang, Dharik S. Mallapragada, Howard K. Gruenspecht, Hannes Pfeifenberger, Paul L. Joskow, and Richard Schmalensee. (2022) "Properties of Deeply Decarbonized Electric Power Systems with Storage" CEEPR WP 2022-003.

Junge, Cristian, Dhark Mallapragada, and Richard Schmalensee (2021) "Energy storage investment and operation in efficient electric power systems," CEEPR WP 2021-001.

Karaduman, Omer. (2020) "Economics of Grid-Scale Energy Storage," mimeo

LaRiviere, Jacob and Xueying Lyu (2022) "Transmission constraints, intermittent renewables and welfare," *Journal of Environmental Economics and Management* 112: 102618

Linn, Joshua, and Kristen McCormack. (2019) "The role of energy markets and environmental regulation in reducing coal-fired plant profits and electricity sector emissions," *Rand Journal of Economics*, 50: 733-767.

McCalley, James, James Bushnell, Venkat Krishnan, and Santiago Lemos-Cano, Santiago. (2012). "Transmission Design at the National Level: Benefits, Risks and Possible Paths Forward," 10.13140/RG.2.1.4567.8241.

Palmer, Karen, Anthony Paul, Matt Woerman, and Daniel C. Steinberg. (2011) "Federal policies or renewable electricity: Impacts and interactions," *Energy Policy*, 3975-3991.

Pommeret, Aude, and Katheline Schubert. (2021) "Optimal energy transition with variable and intermittent renewable electricity generation," forthcoming, *Journal of Economic Dynamics and Control*.

Powell, Siobhan, Gustavo Vianna Cezar, Liang Min, Ines M.L.Azevedo, and Ram Rajagopal. (2022) "Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption," *Nature Energy*, DOI: https://doi.org/10.1038/s41560-022-01105-7.

Raichur, V., D. Callaway, and S. Skerlos. (2015) "Estimating Emissions from Electricity Generation using Electricity Dispatch Models: The Importance of System Operating Constraints," *Journal of Industrial Ecology*, 20(1) 42-53.

Reguant, Mar. (2019) "The efficiency and sectoral distributional impacts of large-scale renewable energy policies," *Journal of the Association of Environment and Resource Economists* 6 (S1): S129-S168.

Shrader, Jeffrey G., Christy Lewis, Gavin McCormick, Isabelle Rabideau, and Burcin Unel. (2021) "(Not so) Clean Peak Energy Standards." *Energy* 225: 120115.

Siler-Evans, K., I. Azevedo, and M. Morgan. (2012) "Marginal Emissions Factors for the U.S. Electricity System," *Environmental Science & Technology*, 46: 4742-4748.

Stellato, B., G. Banjac, P. Goulart, A. Bemporad, and S. Boyd. (2020) "OSQP: an operator splitting solver for quadratic programs." *Mathematical Programming Computation*, 12: 637-672.

Stock, James H., and Daniel N. Stuart. (2021) "Robust decarbonization of the US power sector: Policy options," NBER working paper 28677.

U.S. Energy Information Administration (2020), " The Electricity Market Module of the National Energy Modeling System: Model Documentation 2020," Washington DC.

U.S. Energy Information Administration (2021) "Levelized Costs of New Generation Resources in the *Annual Energy Outlook 2021*," `https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf`, accessed February 2021.

U.S. Environmental Protection Agency (2020) "Greenhouse Gas Emissions: Sources of Greenhouse Gas Emissions," `https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions`.

Weber, Paige and Matt Woerman (2022) "Decomposing the Effect of Renewables on the Electricity Sector," mimeo.

Appendix

A.1 Proofs

Lemma 1 *If $c_i > c_{i'}$ and $q_{it} > 0$, then $q_{i't} = f_{i't}K_{i'}$.*

Proof: Suppose $q_{i't} < f_{i't}K_{i'}$. This implies that $\lambda_{i't} = 0$ which then implies that $p_t \leq c_{i'}$. But $q_{it} > 0$ implies that $p_t = c_i + \lambda_{it} \geq c_i$, which contradicts the assumption $c_i > c_{i'}$. ■

Lemma 2 *If $\sum_i f_{it}K_i > b_t$, then $p_t = \min_i\{\max\{c_i, U'(\sum_{i'\leq i} f_{i't}K_{i'} - b_t)\}\}$.*

Proof: For notational simplicity, assume the technologies have unique costs. Because Lemma 1 implies a unique ordering of the technologies, let $\rho_{it} \equiv U'(\sum_{i'\leq i} f_{i't}K_{i'} - b_t)$ be the marginal benefit if all technologies with operating cost less than or equal to c_i generate at capacity and if net battery charging is b_t. Falling marginal benefit implies that $\rho_{it} > \rho_{(i+1)t}$ for all i. Moreover, it is easy to show that technology i operates at capacity in period t if $\rho_{it} > c_i$.

Let technology ι be the highest cost technology with $q_{\iota t} > 0$ in period t. It is easy to see that $\rho_{\iota t} < c_{\iota+1}$ (otherwise technology $\iota + 1$ would be utilized) and that $\rho_{(\iota-1)t} > c_\iota$ (otherwise technology ι would not be utilitized).

For technology ι, we know that the electricity price is $p_t = c_\iota$ if $c_\iota > \rho_{\iota t}$ and $p_t = \rho_{\iota t}$ if $\rho_{\iota t} > c_\iota$. This implies that $p_t = \max\{c_\iota, \rho_{\iota t}\}$. Now for technology $i < \iota$, generation is at capacity so $\max\{c_i, \rho_{it}\} = \rho_{it}$. Alternatively, for technology $i > \iota$, generation is zero, which is less than capacity, so $\max\{c_i, \rho_{it}\} = c_i$. Combining implies that $\min_i\{\max\{c_i, \rho_{it}\}\} = \min\{\rho_{1t}, \rho_{2t}, ..., \rho_{(\iota-1)t}, p_t, c_{(\iota+1)}, c_{(\iota+2)}, ..., c_I\} = p_t$.■

Lemma 3 *If $S_t = 0$, then $p_{t+1} \leq p_t$. If $0 < S_t < \bar{S}$, then $p_{t+1} = p_t$. If $S_t = \bar{S}$, then $p_{t+1} \geq p_t$.*

Proof: First note that $\phi_t = p_t$. If $S_t = 0$, then $\mu_t = 0$, so the first order condition inequality directly implies that $p_{t+1} - p_t = \phi_{t+1} - \phi_t \leq 0$. If $0 < S_t < \bar{S}$, then $\mu_t = 0$ and the inequality binds from the complementary slackness condition so $p_{t+1} - p_t = 0$. If $S_t = \bar{S}$, then $\mu_t \geq 0$ and $0 = p_{t+1} - p_t - \mu_t \leq p_{t+1} - p_t$, so $p_{t+1} \geq p_t$. ■

Proposition 1 *The derivatives can be written:*

$$d\mathcal{L}/dK_i = \sum_t \max\{p_t - c_i, 0\} f_{it} - r_i = \left(\sum_t (p_t - c_i) q_{it} - r_i K_i \right) / K_i.$$

and $d\mathcal{L}/d\bar{S} = \sum_t -p_t b_t / \bar{S} - r_s$.

Proof: From the first-order conditions, we have that $p_t - c_i \leq \lambda_{it}$. Because $\lambda_{it} \geq 0$ we have $\lambda_{it} \geq \max\{p_t - c_i, 0\}$. Proof by contradiction shows that $\lambda_{it} = \max\{p_t - c_i, 0\}$. Summing over all t establishes the first formula.[52] The second formula follows because $q_{it} = 0$ if $p_t < c_i$, $q_{it} = f_{it} K_i$ if $p_t > c_i$ and $q_{it} \in [0, f_{it} K_i]$ if $p_t = c_i$. For each of these three cases: first, $p_t < c_i$ implies $\max\{p_t - c_i, 0\} f_{it} = 0 = (p_t - c_i) q_{it}$; second $p_t = c_i$ implies $\max\{p_t - c_i, 0\} f_{it} = 0 = (p_t - c_i) q_{it}$; and third $p_t > c_i$ implies $\max\{p_t - c_i, 0\} f_{it} = (p_t - c_i) f_{it} = (p_t - c_i) q_{it} / K_i$. Summing over all t establishes the second formula.

For the battery, Lemma 3 allows us to identify a charging cycle, C: the time period over which the price falls when the battery is empty, the price is flat while the battery charges, the price increases while the battery is full, and then the price is flat while the battery discharges completely. For this charging cycle C, let $\underline{p}$ be the lower price when the price battery is charging, and let $\bar{p}$ be the higher price when then battery discharges. To evaluate $\sum_{t \in C} \mu_t$, first note that $\mu_t = 0$ if $S_t < \bar{S}$ and $\mu_t = p_{t+1} - p_t$ if $S_t = \bar{S}$. In the charging cycle, $\mu_t = 0$ except when the price is rising. During this time, the sequence of μ_t will be $p_{t_1} - \underline{p}$, $p_{t_2} - p_{t_1}$, $p_{t_3} - p_{t_2}$, ..., $\bar{p} - p_{t_n}$, which implies that $\sum_{t \in C} \mu_t = \bar{p} - \underline{p}$. To evaluate $\sum_{t \in C} -p_t b_t$, first note that b_t is zero while the price is falling. Then while the price is flat and the battery is charging, $b_t > 0$ and $\sum -p_t b_t = -\underline{p}\bar{S}$. While the price is rising $b_t = 0$ so $\sum -p_t b_t = 0$. Finally while the price is flat and the batter is discharging, $b_t < 0$ and $\sum -p_t b_t = \bar{p}\bar{S}$. Thus for the charging cycle C, $\sum_{t \in C} -p_t b_t = (\bar{p} - \underline{p})\bar{S}$. Dividing by $\bar{S}$ and summing over all charging cycles establishes the result.■

[52]Suppose $\lambda_{it} > \max\{p_t - c_i, 0\}$. Then $\lambda_{it} > 0$ which implies that $q_{it} = f_{it} K_i > 0$ which implies $\lambda_{it} = p_t - c_i$ which is a contradiction.

Result 1 *If carbon taxes increase, $\Delta\tau > 0$, then emissions decrease, $\Delta \sum_i \sum_t \beta_i q_{it} < 0$, but total electricity consumption can increase or decrease, i.e., $\Delta \sum_t Q_t \lesseqgtr 0$.*

Proof: The first statement follows directly from the increase in costs of any polluting technology.

To show that total electricity consumption can increase or decrease, consider a two period model with two dispatchable technologies. Assume technology 1 has zero operating cost and zero emissions, but technology 2 has positive operating cost and positive emissions. Let H indicate the high demand period and L indicate the low demand period. It is easy to verify that both technologies are used and the equilibrium prices are $p_H = c_2 + \beta_2\tau + r_2$ and $p_L = r_1 - r_2 - c_2 - \beta_2\tau$ if $D_L(p_L) < D_H(p_H)$ and $p_L < c_2 + \beta_2\tau$. Now consider $\Delta\tau > 0$. Clearly $\Delta p_H = \beta_2\Delta\tau > 0$ and $\Delta p_L = -\beta_2\Delta\tau < 0$ which implies that $\Delta(D_H(p_H) + D_L(p_L)) \approx D'_H\Delta p_H + D'_L\Delta p_L = \beta_2\Delta\tau(D'_H - D'_L)$ which can be positive or negative. For example, if the demand is period L is very elastic, then $(D'_H - D'_L) > 0$. In this case, the increase in demand in period L exceeds the decrease in demand in period H so total consumption increases.■

Result 3 *If the capital costs of storage, r_s, decreases, renewable capacity can increase or decrease. If $r_s = 0$, then the equilibrium electricity price is the same in each period, i.e., $p_t = \bar{p}$ for all t, where $\bar{p}$ is given by*

$$\bar{p} = \min_i \{c_i + \frac{r_i}{\sum_t f_{it}}\}.$$

Moreover, if the levelized cost, $c_i + \frac{r_i}{\sum_t f_{it}}$, is unique across technologies, then the capacity of the technology i that satisfies the minimum is given by $K_i = \frac{\sum_t D_t(\bar{p})}{\sum_t f_{it}}$.

Proof: We begin by showing that if $r_s = 0$, then p_t is constant for all t. Suppose $p_t > p_{t'}$ for some t and t'. This implies that $U'_t(Q_t) > U'_{t'}(Q_{t'})$ so the objective in (2) could be increased by marginally increasing Q_t and decreasing $Q_{t'}$. Because $r_s = 0$, this marginal change is feasibly by keeping q_{it} fixed and (costlessly) increasing $\bar{S}$ if necessary. Therefore, p_t is constant at some value $\bar{p}$.

Because price is constant, Prop. 1 and Eq. (7) imply $dL/dK_i = \sum_t \max\{p_t - c_i, 0\} f_{it} - r_i = (\bar{p} - c_i)\sum_t f_{it} - r_i \leq 0$ for all i which implies that $\bar{p} = \min_i\{c_i + \frac{r_i}{\sum_t f_{it}}\}$.

To determine the optimal capacity, note that consumption Q_t is determined by $U_t'(Q_t) = \bar{p}$ so annual consumption is $\sum_t Q_t = \sum_t D_t(\bar{p})$. The perfect battery implies that generation from the single technology is always at capacity. Annual consumption equal to annual generation implies that $\sum_t D_t(\bar{p}) = \sum_t f_{it} K_i$ which can be solved for K_i.

To show that renewable capacity can increase or decrease if r_s decreases, consider a two period model with two technologies: gas, g, and renewable, r, where renewable generation is only available in the high-demand period. Suppose initially the cost of storage r_s is large enough that storage will not be used. If $c_g + r_g > r_r > c_g$, then it is easy to verify that the equilibrium has positive capacity for both technologies and has a high-demand period price of $p_H = r_r$ and a low-demand period price of $p_L = c_g+(r_g+c_g-r_r)$ and capacities $K_g = D_L(p_L)$ and $K_r = D_H(p_H)-K_g$. If r_s decreases to zero, the equilibrium price approaches $\min\{c_g+r_g/2, r_r\}$. If $c_g + r_g/2 < r_r$, then gas is the only technology used, and renewable capacity must decrease. Conversely, if $c_g + r_g/2 > r_r$, then only renewable generation is used, and renewable capacity must increase.[53] ■

Result 2 *If the capital cost of renewables decreases then carbon emissions can increase or decrease, i.e.,* $\Delta \sum_i \sum_t \beta_i q_{it} \lessgtr 0$.

Proof: Proving that cheaper renewables decrease carbon emissions is straightforward. Here we prove that $\Delta \sum_i \sum_t \beta_i q_{it}$ can be positive with an example with two time periods, A and B, equal demand in each time period, and three technologies. Technology 1 (renewable) is available only in period A, *i.e.,* has capacity factors $f_{1A} = 1$ and $f_{1B} = 0$. Technology 2 (nuclear) and Technology 3 (gas) are dispatchable. Assume $c_1 = c_2 = 0$ and $\beta_1 = \beta_2 = 0$ but $c_3 > 0$ and $\beta_3 > 0$. Further assume $c_3 + r_3 < r_2 < 2c_3 + r_3$ which implies that Technology 3 is cheaper for satisfying demand in only one period, but Technology 2 is cheaper for satisfying two periods.

If r_1 is large such that $r_1 > r_2/2$, then it is easy to see that the equilibrium has only Technology 2 with prices $p_A = p_B = r_2/2$ and zero emissions. If r_1 falls slightly such that $r_2/2 > r_1 > r_2 - c_3 - r_3$, then the equilibrium has Technologies 1 and 2, has prices $p_A = r_1$ and

[53] For example, suppose $D_H = 6 - p_H$; $D_L = 5 - p_L$; $c_g = 1$; and $r_r = 2$. If $r_g = 3$, then without storage $p_H = 2; p_L = 3$ and storage increases K_r. On the other hand, if $r_g = 1.5$, then without storage $p_H = 2; p_L = 1.5$ and storage decreases K_r.

$p_B = r_2 - r_1$, and still has zero emissions. However, if r_1 falls further such that $r_1 < r_2 - c_3 - r_3$, then the equilibrium has Technologies 1 and 3, has prices $p_A = r_1$ and $p_B = c_3 + r_3$, and has *positive* emissions. ■

Result 4 *If electricity demand increases in some period(s), then carbon emissions can increase or decrease, i.e.,* $\Delta \sum_i \sum_t \beta_i q_{it} \lesseqgtr 0$.

Proof: As in the preceding proof, consider a two period model with two dispatchable technologies. Assume technology 1 has zero operating cost and zero emissions, but technology 2 has positive operating cost and positive emissions. Let H indicate the high demand period and L indicate the low demand period. With no taxes, it is easy to verify that both technologies are used and the equilibrium prices are $p_H = c_2 + r_2$ and $p_L = r_1 - r_2 - c_2$ if $D_L(p_L) < D_H(p_H)$ and $p_L < c_2$. Note also that $K_1 = D_L(p_L)$ and $K_1 + K_2 = D_H(p_H)$ so emissions are only in period H and are $\beta_2 K_2$. Importantly, note that p_L and p_H are determined by r_i and c_i so they are not affected by increments to demand.

Now consider an increment δ to demand in period H. Since prices are unaffected, K_1 is also unaffected, and $\Delta K_2 = \delta > 0$. But this implies that the change in emissions, $\beta\delta$, is positive.

Now consider an increment δ to demand in period L. Since p_L is unaffected, $\Delta K_1 = \delta$. But because p_H is also unaffected, we have $\Delta K_2 = -\delta < 0$, which implies that the change in emissions, $-\beta\delta$, is negative.■

A.2 Renewable capacity factors for missing regions

EIA 930 is missing hourly solar generation for New York and hourly wind generation for Carolinas, Florida, SouthEast, and Tennessee. We estimate the missing capacity factors as follows. For New York solar, we use the NREL National Solar Radiation Database (NSRDB) which provides half hour values for Direct Normal Irradiance (DNI) in watts per square meter. We use Boston (ISONE) and Philadelphia (PJM/MIDA) as comparisons to generate capacity factors for New York (NYISO). First we collapse the DNI data by hourly average and market. We then regress capacity factor on DNI for ISONE and PJM/MIDA for daylight hours. Using these regression results, we predict capacity factors for NYISO and bound these predictions between 0 and 1 (set to zero if DNI is zero).

For the wind capacity factors in Carolinas, Florida, SouthEast, and Tennessee, we collect data on wind speed from NREL (for the year 2014) by site and by hour for wind potential at 80 meters.[54] For every county centroid in the U.S., we find the NREL site closest to the centroid, giving one observation per county per hour. Then we convert wind speed into an estimated capacity factor by county by hour (ECFH).[55] Next we collapse to an annual average by county, de-mean by state, and create deciles of the residual for each county.

EPA's EGRID 2014 data indicates which counties actually have wind turbines. We calculate what share of counties with wind turbines that are in each decile. In other words, we determine the probability of building a turbine in each decile (PBTEC). Now using the ECFH, we take the weighted average across a region using PBTEC. This gives us capacity factors at the region hourly level, which we call RECFH. The last step is to compare the predicted capacity factors in the regions for which we have actual capacity factor data for 2019. We calculate the average difference between the 2019 data and the 2014 predictions, by month and hour. Then we add this "bias" back onto the RECFH in regions for which we do not have actual 2019 capacity factor data. Finally these predictions are bounded by zero and one.

A.3 Calculation of Welfare gains from 100% EV Fleet

Consider an initial equilibrium in which the electricity sector is defined by the model in the paper and the automobile transportation sector consists of only gasoline vehicles. Welfare associated with electricity use is gross consumer surplus (CS_e) minus costs of electricity $Cost_e$ (the sum of operating and capital costs) minus damages from electricity emissions D_e. Welfare associated with gasoline vehicle use is given by gross consumer surplus (CS_{GV}) minus operating costs ($Cost_{GV}$) minus damages from emissions (D_{GV}) minus gasoline vehicle

[54] https://www.nrel.gov/grid/wind-toolkit.html

[55] See equation (23) in Dioyke, C, 2019, "A new approximate capacity factor method for matching wind turbines to a site: case study of Humber region, UK", *International Journal of Energy and Environmental Engineering*, `https://doi.org/10.1007/s40095-019-00320-5`.

capital costs (V_{GV}). In the initial equilibrium total welfare is

$$W = (CS_e - Cost_e - D_e) + (CS_{GV} - Cost_{GV} - D_{GV} - V_{GV}).$$

Next consider a new equilibrium in which the gasoline vehicle fleet is replaced by an electric vehicle fleet (EV). Total welfare in the new equilibrium is

$$W = (CS_e + CS_{EV} - Cost_e - D_e) - V_{EV},$$

where CS_{EV} is the gross consumer surplus from driving EVs and V_{EV} is the capital cost of EVs. Taking the difference between the two welfare equations gives

$$\Delta = (\Delta CS_e - \Delta Cost_e - \Delta D_e) + (CS_{EV} - CS_{GV}) + Cost_{GV} + D_{GV} - (V_{EV} - V_{GV}).$$

The first term on the right hand side calculated from the model in the paper. We assume that the consumer surplus of driving the two types of cars is approximately the same, and we determine the cost of operating the gasoline fleet, the damages from operating the gasoline fleet, and the capital premium for electric vehicles using data from Holland et al. (2021).

$$Cost_{GV} = \frac{313\text{g/mile}}{8887\text{g/gallon}} * 2600.406 \text{ billion miles} * \$3/\text{gallon} = \$274.76 \text{ billion},$$

$$D_{GV} = 313\text{g/mile} * \frac{\text{metric ton}}{1000000g} * SCC * 2600.406 \text{ billion miles},$$

$$V_{EV} - V_{GV} = \$10689.57 * 17 \text{ million cars/year} = \$181.72 \text{ billion}.$$

Online Appendices

O.A.1 Solution algorithm using gradient search

Without a storage technology, the gradient search algorithm is straightforward. For a given vector of capacities, Lemma 2 determines the electricity price for each period. Eqs. 3 and 4 and Lemma 2, then imply electricity consumption and generation from each technology. Adding up across all periods gives profit for each technology, which gives the gradient vector (Proposition 1). From here, a standard gradient search optimization is computationally efficient. With storage technology, we nest a storage optimization algorithm within the gradient search algorithm. For a feasible vector of net charges to the battery, Lemma 2 determines the electricity price for each period, which implies consumption and generation in each period, and from which we can calculate the planner's objective in (9). We then find the vector of net charges that that maximizes this sum by using a dynamic programming algorithm. The state variable is the discretized state of the battery and the optimization in each period determines the net charge for the battery in that period. Based on the optimal net charge vector, we can calculate the profit for each technology and for storage, which gives the gradient vector including storage (Proposition 1). We then use a gradient search optimization with the nested battery optimization to calculate the optimal capacities for each generation technology and for the storage technology.

O.A.2 Aggregation using NEMS time periods

A key feature of our model is that we specify a rich set of representative time periods for demand and renewables. By basing our calibration on observed hourly demand and renewable availability, our model allows for realistic correlations between demand and renewable availability. Other models consider far fewer representative time periods, which effectively assumes that electricity demand and renewable availability are constant over many hours. For example, the base model in NEMS uses only nine representative time periods for each region with additional submodules available for better modeling of renewables. To see the effects of coarsening the number of time periods, we apply the NEMS methodology for selecting time periods to our data and re-run the analysis using nine distinct demand curves (instead of 8760) and nine capacity factors (instead of 8760) for solar and for wind. The nine time periods in NEMS are constructed from three seasons (Summer, Winter, Fall/Spring), and three time periods within each season (Peak, Intermediate, Base). The Peak time period consists of hours in season for which electricity load is in the 99th percentile or above, the Intermediate time period consists of hours for which the electricity load is between the 50th and the 99th percentile, and the Base consists of hours in which the electricity load is in the 50th percentile or below (see EIA (2020), pg. 32). Following these definitions, we coarsen our data by taking the average of electricity load and price over all hours in a NEMS period and use these averages to define nine distinct demand curves. We use the same procedure to coarsen data on renewable capacity factors.[56]

Using these coarsened time periods, we first analyze the effects of carbon pricing. Figure O.A.5 shows that a $50 carbon tax almost completely decarbonizes electricity with almost all electricity from wind or solar. This result is quite different from our main results in Figure 2 but is similar to Stock and Stuart (2021) who use a modified version of the NREL ReEDS model and find that a $40 carbon tax achieves robust decarbonization. Unfortunately, the levels of renewable generation from our model with the NEMS time periods are quite unrealistic. Figure O.A.6 shows the results by region and shows regions, namely, Florida and SouthEast, which are entirely solar, which is infeasible without substantial electricity storage. While these differences warrant further study, they are indicative of the importance of modeling a rich set of representative time periods for demand and renewables.

O.A.3 Comparison to a capacity expansion model

In our model, consumers respond to real-time electricity prices. If the price of electricity increases, then the consumption of electricity decreases, albeit by a small amount, given our assumed price elasticity of $-.15$. Thus we have a consumer benefit function and the planner maximizes the difference between benefits and costs. In contrast, papers such as Junge et al. (2022) employ a capacity expansion model. Here electricity demand is perfectly inelastic

[56]Since 2019 NEMS has added a ReStore submodule with 576 hours to model the usage of storage and renewables that they then feed back into the nine demand functions.

and the planner minimizes the cost of meeting the fixed quantity of electricity demanded. The inflexibility of demand may give rise to greater benefits from battery storage. To test this hypothesis, we consider a capacity expansion version of the long-run model in the main text. Here the planner solves

$$\max_{q_{it}, b_t, S_t, K_i, \bar{S}} \sum_t \left[- \sum_i c_i q_{it} \right] - \sum_i r_i K_i - r_s \bar{S}, \tag{9}$$

subject to the same constraint set as in the main paper except that Q_t is no longer a choice variable and is fixed at $\bar{Q}_t$ so that the production constraint becomes

$$\bar{Q}_t + b_t \leq \sum_i q_{it}.$$

We solve this problem by employing a standard linear programming algorithm and we apply the exact same simulation data as in the main paper. The results are shown in Table O.A.12. Comparing the results to Table O.A.6 we see that fixing demand does generally give greater benefits to batteries.

O.A.4 Ramping constraints

Fossil fuel technologies differ in their ability to quickly respond to increases or decreases in the demand for their electricity. In our simulation, we consider two gas technologies: combined cycle and peaker. Peaker plants can respond quicker than combined cycle plants so we consider ramping constraints on the latter. Denoting this technology by j, we add the following constraint to the planner's problem:

$$q_{j,t} \leq q_{j,t-1} + \kappa K_i.$$

The ramping constraint is fixed as a percentage of capacity. Generation can't increase by more than this amount from one hour to the next. Figure O.A.18 shows the results for a variety of values for κ under the assumption of a 50% renewable capital cost reduction. Even a strict value of $\kappa = 0.1$ (which implies 10 hours for generation to reach capacity) has little effect on generation. Battery capacity does increase by 45% and battery utilization increases by 27% when moving from $\kappa = 1$ (no ramping constraint) to $\kappa = 0.1$.

To further understand the effects of ramping constraints, we consider hourly data from the California region. Figure O.A.19a shows the well known "duck curve", defined as consumption minus renewable generation. The curve is quite low during the middle of the day and then increases rapidly in the late afternoon and early evening. The concern with the duck curve is that fossil generation must ramp quickly to meet this rise. Also shown is an even more pronounced duck curve that would result if prices did not change across hours. To generate this curve we utilize the long run equilibrium values for capacity but then calculate short-run consumption in each hour under the assumption that prices are fixed at the long run average cost of generation. It illustrates that if we were to remove the demand elasticity from our model, then the concern about ramping constraints becomes more severe.

The kernal density for ramp rates ($\frac{q_{j,t}-q_{j,t-1}}{K_j}$) for combined cycle gas generation is shown in Figure O.A.19b. With no ramping constraint, even though the duck curve has a steep slope, the density has only a small amount of mass at ramping rates greater than 0.5. With the ramping constraints in place, the distribution is truncated at the value of κ. The truncation only as a small effect for $\kappa = 0.3$, but the effect is quite pronounced for $\kappa = 0.1$. The effect of the ramping constraints on the capacity utilization of combined cycle gas plants is shown in Figure O.A.19c. Again we see that moving from $\kappa = 1$ to $\kappa = 0.3$ has little effect. Relative to either of these cases, when $\kappa = 0.1$, gas plant utilization stays higher throughout the middle of the day.

We see that ramping constraints have little effect on the overall generation technology mix. As the ramping constraints become more severe, battery capacity is increased and the utilization of combined cycle gas plants over the hours in a day changes to some degree. As a result of these adaptations, the welfare loss due to ramping is trivial.

O.A.5 Upward sloping supply curve

In our baseline model, the capital costs of renewable capacity are constant with respect to the amount of capacity. In practice, renewable capital costs may increase as capacity increases due to increasing costs of materials for construction and/or decreasing suitability of sites for locating the solar panels or wind turbines. Let the cost per unit of capacity is given by

$$r_i + \eta_i K_i.$$

Here the value for capital costs r_i used in our baseline model corresponds to the initial capital costs when desired capacity is zero. Increases in desired capacity linearly increases capital costs per unit of capacity. Thus capital costs $r_i K_i$ in the planner's problem is replaced with

$$(r_i + \eta_i K_i)K_i.$$

In their analysis of renewable resource integration into the electricity grid, Borenstein and Kellogg (2022) assume that renewable costs increase by 42 percent as the quantity supplied increases from baseline to the maximum in their model. Using this 42 percent increase as a benchmark, we determine the value for η as 1.01 dollars per MW squared for solar and 1.0 dollars per MW squared for wind. The generation by fuel type for various values of the renewable subsidy is shown in Figure O.A.20. Comparing this to Panel A of Figure 4 in the main text shows that consideration of an upward sloping supply curve significantly reduces the amount of generation from wind and solar.

O.A.6 Consideration of generation from coal

Using the same EIA data source as for the other technologies, the capital cost of new coal generation is \$374,608 per MW and the operating cost is \$22.48 per MWh. As discussed in the main text, coal is dominated by natural gas at our baseline cost values for all technologies. To see the degree to which cost values have to change before coal becomes a viable generation technology, we consider a sensitivity analysis in which we increase the ratio of operating cost of gas generation to operating cost of coal generation or decrease the ratio of capital cost of coal generation to capital cost of gas generation. The results are shown in Figure O.A.21. Keeping the capital cost ratio at baseline, the operating cost ratio of gas to coal would have to increase to 2.85 (a factor of 2.4 from baseline of 1.19) before any coal generation is used at all in the long run equilibrium. Keeping the operating cost ratio at baseline, the capital cost ratio of coal to gas would have to decrease to 1.41 (a seventy percent decrease from baseline of 4.71) before any coal generation is used at all. In our baseline, the vast majority of generation is from natural gas. In the event that gas costs increase significantly from baseline and coal capital costs decrease significantly from baseline, much of this generation would switch from gas to coal.

Online Appendix Tables

Table O.A.1: Summary statistics of hourly capacity factors and observed demand conditions

Region	Capacity Factors Solar		Capacity Factors Wind		Observed Demand		Observed Price	
East								
Carolinas	0.21	(0.28)	0.27	(0.16)	25,460	(5,443)	25.83	(7.35)
Central	0.24	(0.31)	0.43	(0.20)	30,839	(5,278)	22.56	(32.08)
Florida	0.23	(0.29)	0.19	(0.09)	27,552	(7,239)	19.55	(4.53)
MidAtlantic	0.19	(0.26)	0.33	(0.22)	91,361	(15,759)	25.47	(20.29)
MidWest	0.18	(0.24)	0.35	(0.19)	80,790	(12,091)	24.85	(17.21)
New England	0.16	(0.24)	0.30	(0.21)	13,503	(2,428)	30.85	(20.29)
New York	0.18	(0.23)	0.31	(0.25)	17,789	(3,198)	25.15	(15.17)
SouthEast	0.23	(0.30)	0.23	(0.14)	27,759	(5,998)	20.39	(2.39)
Tennessee	0.21	(0.30)	0.27	(0.18)	18,190	(3,743)	22.13	(8.41)
West								
California	0.27	(0.33)	0.27	(0.19)	30,187	(6,149)	35.23	(26.20)
NorthWest	0.27	(0.33)	0.31	(0.15)	39,982	(5,526)	21.13	(21.72)
SouthWest	0.29	(0.32)	0.38	(0.21)	11,923	(3,406)	27.48	(5.19)
Texas								
Texas	0.24	(0.31)	0.40	(0.21)	43,798	(9,769)	29.69	(70.63)

Notes: Unweighted mean over 8760 hours with standard deviation in parenthesis. Observed demand in MWh, price in $ per MWh. Prices are truncated at $1000 and $10 per MWh.

Table O.A.2: Benefits of carbon pricing

Carbon Tax ($/ton)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Welfare Gains ($ billions) for SCC of $0	$50	$100	$150	$200
Panel A: Linear Demand							
0	37.65	1,104	**0.0**	0.0	0.0	0.0	0.0
50	50.81	537	-16.4	**11.9**	40.2	68.6	96.9
100	55.48	221	-40.2	4.0	**48.1**	92.3	136.4
150	55.57	46	-61.1	-8.2	44.7	**97.6**	150.5
200	54.82	2	-68.4	-13.3	41.8	96.8	**151.9**
Panel B: Iso-Elastic Demand							
0	38.26	1,151	**0.0**	0.0	0.0	0.0	0.0
50	51.85	649	-14.7	**10.4**	35.6	60.7	85.9
100	57.64	326	-39.1	2.1	**43.4**	84.6	125.9
150	59.33	128	-62.9	-11.8	39.4	**90.6**	141.7
200	59.72	60	-74.3	-19.8	34.8	89.3	**143.9**

Notes: Baseline parameterization (linear or iso-elastic demand, storage, no interregional transmission). Electricity price is the quantity-weighted average price. Welfare gains are relative to the baseline without carbon taxes and include lost private surplus plus gains from carbon tax revenue and from reduced carbon emissions evaluated at the assumed SCC. First-best welfare gains are in bold.

Table O.A.3: Benefits of reducing renewable capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill
Panel A: Linear Demand								
0	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0
25	36.49	895	3.7	14.1	24.6	35.0	45.4	7.9
50	30.62	433	21.7	55.3	88.8	122.4	155.9	52.0
75	19.92	147	57.9	105.7	153.6	201.4	249.2	147.1
95	6.19	10	113.8	168.5	223.2	277.9	332.5	417.0
Panel B: Iso-Elastic Demand								
0	38.26	1,151	0.0	0.0	0.0	0.0	0.0	0.0
25	37.11	956	3.6	13.3	23.1	32.8	42.6	7.4
50	31.02	476	21.4	55.1	88.9	122.6	156.4	52.9
75	18.28	200	58.6	106.2	153.8	201.4	249.0	149.9
95	4.09	44	114.9	170.3	225.7	281.1	336.5	430.7

Notes: Baseline parameterization. Electricity price is the quantity-weighted average price. Benefits are relative to the baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent renewable capacity without innovation.

Table O.A.4: Benefits of reducing nuclear capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill
0	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0
25	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0
40	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0
50	34.70	155	8.5	55.9	103.3	150.7	198.1	90.0
75	19.10	4	63.5	118.5	173.5	228.5	283.5	188.8

Notes: Baseline parameterization. Electricity price is the quantity-weighted average price. Benefits are relative to the baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent nuclear capacity without innovation.

Table O.A.5: Benefits of increasing transmission

Transmission Scenario	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill
Panel A: Baseline renewable capital costs								
Baseline	37.65	1,104	0.0	0.0	0.0	0.0	0.0	N.A.
Scenario 2	37.68	1,078	1.7	3.0	4.3	5.5	6.8	N.A.
Scenario 3	37.94	1,057	2.9	5.3	7.6	10.0	12.3	N.A.
Scenario 4	37.07	1,056	4.1	6.5	8.9	11.3	13.7	N.A.
Scenario 5	36.04	938	7.6	15.9	24.2	32.5	40.8	N.A.
Panel B: 25% reduction in renewable capital costs								
Scenario 1	36.49	895	3.9	14.4	24.8	35.3	45.7	7.9
Scenario 2	34.62	740	9.1	27.3	45.5	63.7	81.9	11.8
Scenario 3	34.08	386	17.0	52.8	88.7	124.6	160.4	21.4
Scenario 4	33.03	361	18.7	55.8	92.9	130.0	167.2	21.9
Scenario 5	30.46	294	24.6	65.0	105.5	146.0	186.4	22.8

Notes: Baseline parameterization. "Subsidy Cost" is the subsidy that would be required to induce an equivalent renewable capacity without innovation. The Baseline (Scenario 1) has 13 distinct transmission regions. Scenario 2 has 5 distinct transmission regions: NE, SE, MW, Texas, and West. Scenario 3 has 3 distinct transmission regions: East, Texas, and West. Scenario 4 has 2 distinct transmission regions: East plus Texas, and West. Scenario 5 has 1 unified transmission region for the whole country.

Table O.A.6: Benefits of reducing battery capital costs and renewable capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Battery	Renew
Panel A: Baseline renewable capital costs									
Baseline	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	37.63	1,101	0.2	0.4	0.5	0.6	0.8	0.3	N.A.
50	37.56	1,100	0.7	0.9	1.1	1.2	1.4	1.5	N.A.
75	37.35	1,106	2.0	1.9	1.7	1.6	1.5	6.8	N.A.
100	35.55	897	11.4	21.7	32.1	42.4	52.8	4,343	N.A.
Panel B: 50% reduction in renewable capital costs									
0	30.62	433	21.7	55.3	88.8	122.4	155.9	0.0	52.0
25	30.52	420	22.2	56.4	90.6	124.8	158.9	0.7	52.5
50	30.26	395	23.4	58.8	94.3	129.7	165.2	3.5	53.7
75	29.29	292	27.0	67.6	108.2	148.7	189.3	20.3	60.0
100	20.80	0	63.5	118.7	173.8	229.0	284.2	8,767	173.2

Notes: Baseline parameterization. Benefits are relative to the baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent battery capacity (Battery) or renewable capacity (Renew) without innovation.

Table O.A.7: Levelized cost and capacities with costless battery capacity

	Levelized Cost ($/MWh)		Generation Capacity (GW)			Battery Capacity (TWh)			Carbon Tax
Region	Solar	Wind	Solar	Wind	Gas	Solar	Wind	Gas	($/Ton)
East									
Carolinas	45.93	55.37	105	74	23	20	21	9	30
Central	39.94	35.16	95	55	24	29	18	9	0
Florida	41.97	81.00	100	77	24	12	11	15	18
MidAtlantic	50.29	45.72	388	230	82	88	95	23	29
MidWest	54.07	43.05	360	196	73	110	70	17	22
New England	59.22	50.06	62	35	12	17	12	5	42
New York	53.62	49.05	64	38	13	13	14	6	39
SouthEast	41.83	66.81	97	76	23	18	18	15	18
Tennessee	45.19	56.56	62	44	14	18	13	7	28
West									
California	35.25	55.52	93	82	25	37	46	19	0
NorthWest	35.20	48.62	79	59	21	38	23	18	0
SouthWest	32.61	40.23	38	28	11	11	13	9	0
Texas									
Texas	38.86	37.84	154	95	39	27	37	27	6

Notes: "Levelized Cost" and "Generation Capacity" are calculated from the formulas in Result 3 assuming baseline renewable costs. Levelized cost for combined cycle gas is $35.75 per MWh. "Generation Capacity" is the capacity, K_i, required from technology i if technology i is the only technology. "Battery Capacity" is the minimum battery capacity, $\bar{S}$, required if technology i is the only technology. "Carbon Tax" is the minimum carbon tax required to make the levelized cost of combined cycle gas greater than the levelized cost of solar or wind. Total U.S. battery storage in 2019 is approximately 0.0017 TWh.

Table O.A.8: Benefits of reducing battery capital costs and solar capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Battery	Solar
Panel A: Baseline solar capital costs									
Baseline	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	37.63	1,101	0.2	0.4	0.5	0.6	0.8	0.3	N.A.
50	37.56	1,100	0.7	0.9	1.1	1.2	1.4	1.5	N.A.
75	37.35	1,106	2.0	1.9	1.7	1.6	1.5	6.8	N.A.
Panel B: 50% reduction in solar capital costs									
0	34.19	788	11.1	26.9	42.7	58.5	74.3	0.0	25.2
25	34.12	775	11.6	28.0	44.4	60.9	77.3	0.6	25.8
50	33.91	741	12.6	30.8	48.9	67.0	85.1	3.5	27.7
75	32.66	571	16.8	43.4	70.1	96.7	123.3	25.5	38.9

Notes: Baseline parameterization. Electricity price is the quantity-weighted average price. Benefits are relative to the baseline and include lost private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent battery capacity (Battery) or solar capacity (Solar) without innovation.

Table O.A.9: Benefits of reducing battery capital costs and wind capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Battery	Wind
Panel A: Baseline wind capital costs									
Baseline	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	37.63	1,101	0.2	0.4	0.5	0.6	0.8	0.3	N.A.
50	37.56	1,100	0.7	0.9	1.1	1.2	1.4	1.5	N.A.
75	37.35	1,106	2.0	1.9	1.7	1.6	1.5	6.8	N.A.
Panel B: 50% reduction in wind capital costs									
0	32.91	559	13.8	41.0	68.3	95.5	122.7	0.0	41.6
25	32.83	552	14.1	41.7	69.3	96.9	124.5	0.5	42.1
50	32.61	538	15.0	43.3	71.6	99.8	128.1	2.8	43.3
75	32.05	508	17.4	47.2	77.0	106.7	136.5	11.3	45.5

Notes: Baseline parameterization. Electricity price is the quantity-weighted average price. Benefits gains are relative to the baseline and include lost private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Costs" is the subsidy that would be required to induce an equivalent battery capacity (Battery) or wind capacity (Wind) without innovation.

Table O.A.10: Benefits of reducing battery capital costs and nuclear capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Battery	Nuclear
Panel A: Baseline nuclear capital costs									
Baseline	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	37.63	1,101	0.2	0.4	0.5	0.6	0.8	0.3	N.A.
50	37.56	1,100	0.7	0.9	1.1	1.2	1.4	1.5	N.A.
75	37.35	1,106	2.0	1.9	1.7	1.6	1.5	6.8	N.A.
Panel B: 50% reduction in nuclear capital costs									
0	34.70	155	8.5	55.9	103.3	150.7	198.1	0.0	90.0
25	34.65	143	8.8	56.8	104.8	152.9	200.9	0.5	90.7
50	34.51	121	9.6	58.7	107.8	157.0	206.1	2.3	92.5
75	34.18	97	11.4	61.7	112.1	162.4	212.7	8.2	95.4

Notes: Baseline parameterization. Electricity price is the quantity-weighted average price. Benefits are relative to the baseline and include lost private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent battery capacity (Battery) or Nuclear capacity (Nuclear) without innovation.

Table O.A.11: Benefits of reducing nuclear capital costs and renewable capital costs

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Renew	Nuclear
Panel A: Baseline nuclear capital costs									
0	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	36.49	895	3.7	14.1	24.6	35.0	45.4	7.9	N.A.
50	30.62	433	21.7	55.3	88.8	122.4	155.9	52.0	N.A.
75	19.92	147	57.9	105.7	153.6	201.4	249.2	147.1	N.A.
Panel B: 50% reduction in nuclear capital costs									
0	34.70	155	8.5	55.9	103.3	150.7	198.1	0.0	90.0
25	34.27	183	10.2	56.2	102.3	148.3	194.4	4.4	76.0
50	30.51	330	22.1	60.8	99.5	138.1	176.8	47.4	15.1
75	19.92	147	57.9	105.7	153.6	201.4	249.2	147.1	0.0

Notes: Baseline parameterization. Benefits are relative to the baseline and include lost private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent renewable capacity (Renew) or nuclear capacity (Nuclear) without innovation.

Table O.A.12: Benefits of reducing battery capital costs and renewable capital costs: Cost minimization

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill Battery	Renew
Panel A: Baseline renewable capital costs									
Baseline	37.72	1,232	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	37.68	1,224	0.2	0.5	0.9	1.2	1.6	0.2	N.A.
50	37.57	1,217	0.6	1.3	2.0	2.8	3.5	1.6	N.A.
75	37.06	1,212	2.6	3.6	4.6	5.5	6.5	12.8	N.A.
100	32.99	990	19.0	31.1	43.1	55.2	67.3	4,569	N.A.
Panel B: 50% reduction in renewable capital costs									
0	33.15	584	18.3	50.7	83.1	115.5	147.9	0.0	46.9
25	32.94	565	19.2	52.6	85.9	119.3	152.6	1.2	48.3
50	32.44	531	21.2	56.3	91.3	126.4	161.4	5.9	50.3
75	31.22	448	26.1	65.3	104.5	143.6	182.8	23.9	55.0
100	19.40	0	73.6	135.2	196.8	258.4	320.0	8,640	78.0

Notes: Baseline parameterization. Benefits are relative to the baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost" is the subsidy that would be required to induce an equivalent battery capacity (Battery) or renewable capacity (Renew) without innovation.

Online Appendix Figures

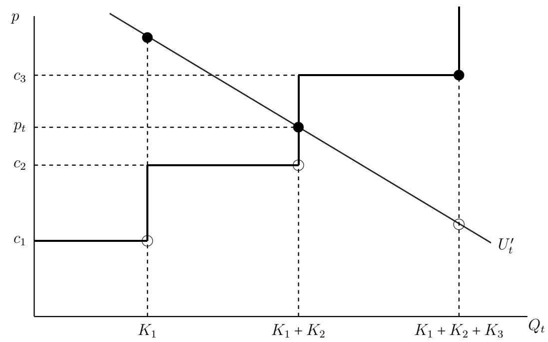


Figure O.A.1: Illustrative supply and demand with market clearing price p_t.

Notes: To illustrate Lemma 2, this figure assumes no storage and three technologies with capacity factors equal to one. The electricity price is determined by the intersection of the smooth demand curve U'_t and the step function supply curve. For this example, the equation for p_t from the lemma is

$$p_t = \min\{\max\{c_1, U'_t(K_1)\}, \max\{c_2, U'_t(K_1 + K_2)\}, \max\{c_3, U'_t(K_1 + K_2 + K_3)\}$$

which is the minimum of three max expressions. The solid and unfilled circles indicate the values to be compared inside each of the max expressions, with the solid circles indicating the resulting maximum values. Thus $p_t = \min\{U'_t(K_1), U'_t(K_1 + K_2), c_3\}$, i.e., the minimum over the solid circles. In the figure, the demand curve intersects the supply curve at the vertical portion corresponding to the total capacity of the first two technologies, i.e. $p_t = U'_t(K_1 + K_2)$.

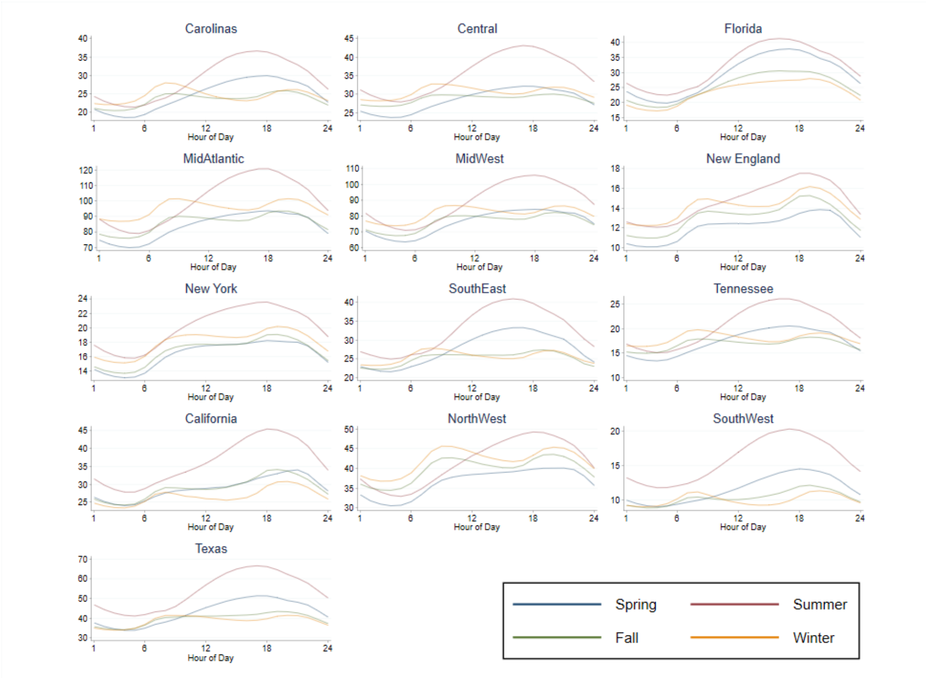


Figure O.A.2: Mean hourly observed demand by season and hour of day for each EIA region.

Notes: Demand in thousands of MWh.

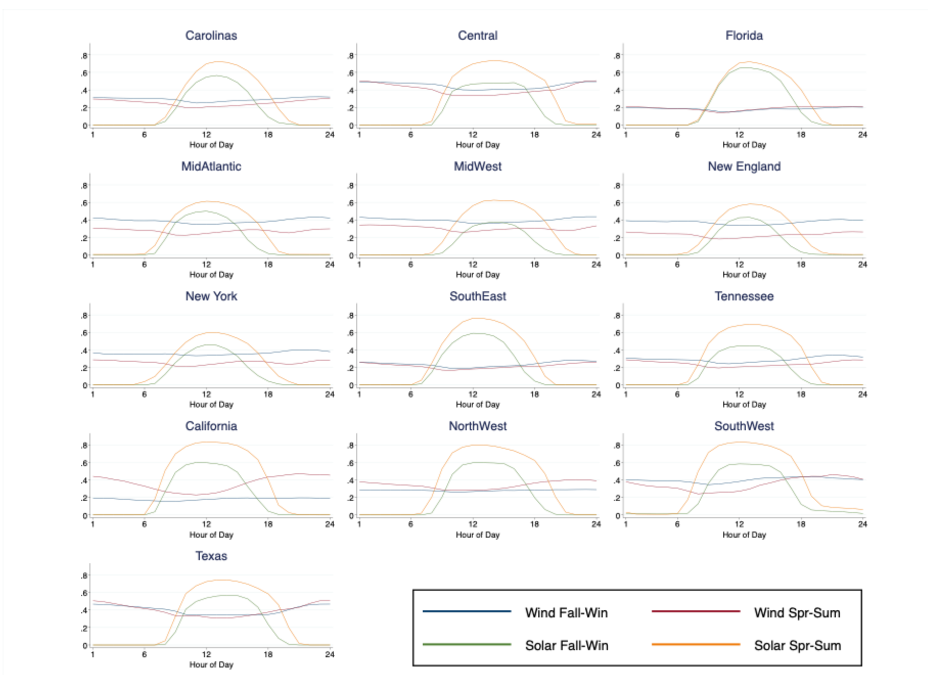


Figure O.A.3: Mean hourly capacity factors by season and hour of day for each EIA region.

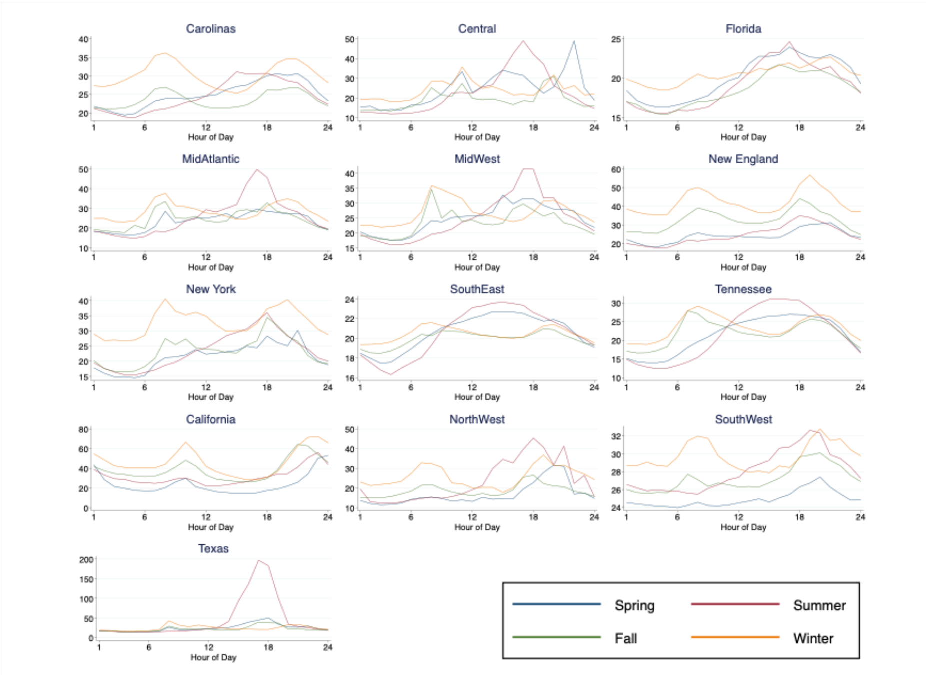


Figure O.A.4: Mean hourly observed price by season for each EIA region.

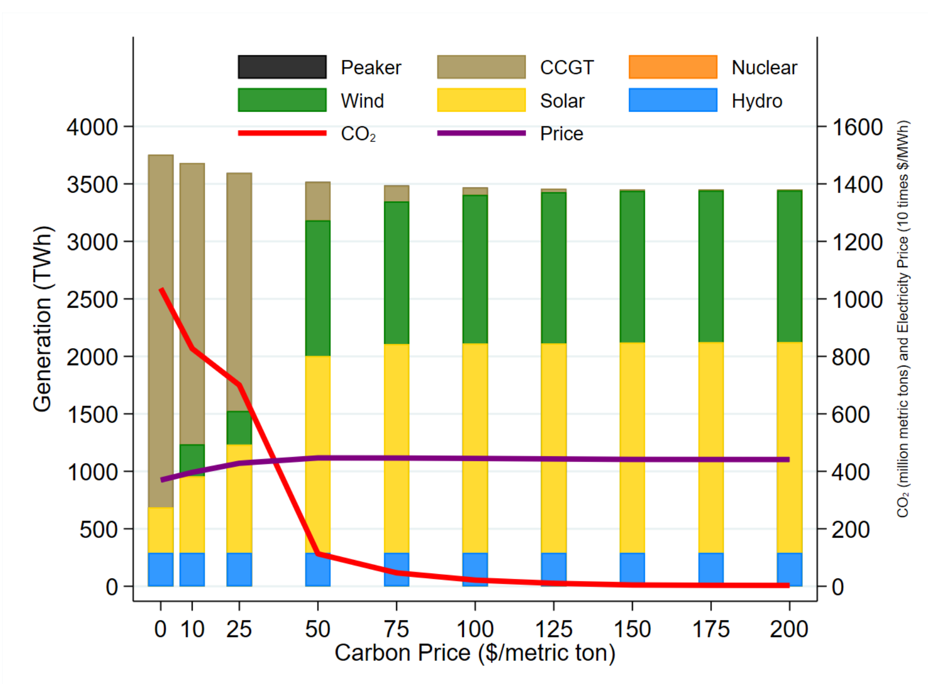


Figure O.A.5: Carbon pricing with NEMS time periods.

Notes: Baseline parameterization for nine NEMS time periods, no battery storage, aggregated across all regions.

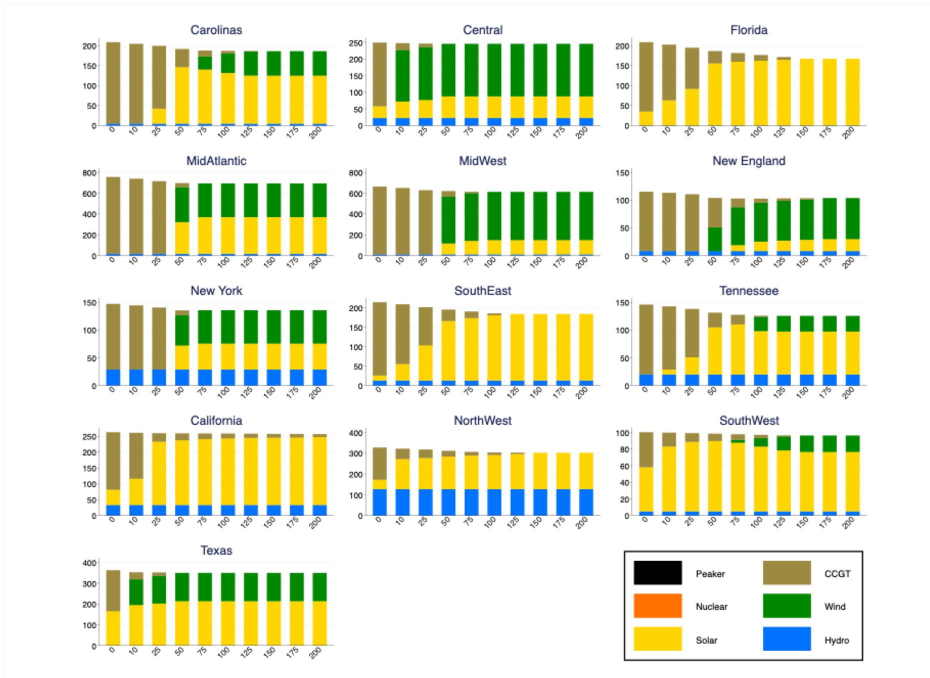


Figure O.A.6: Carbon pricing with NEMS time periods for each region

Notes: Baseline parameterization for nine NEMS time periods and no battery storage.

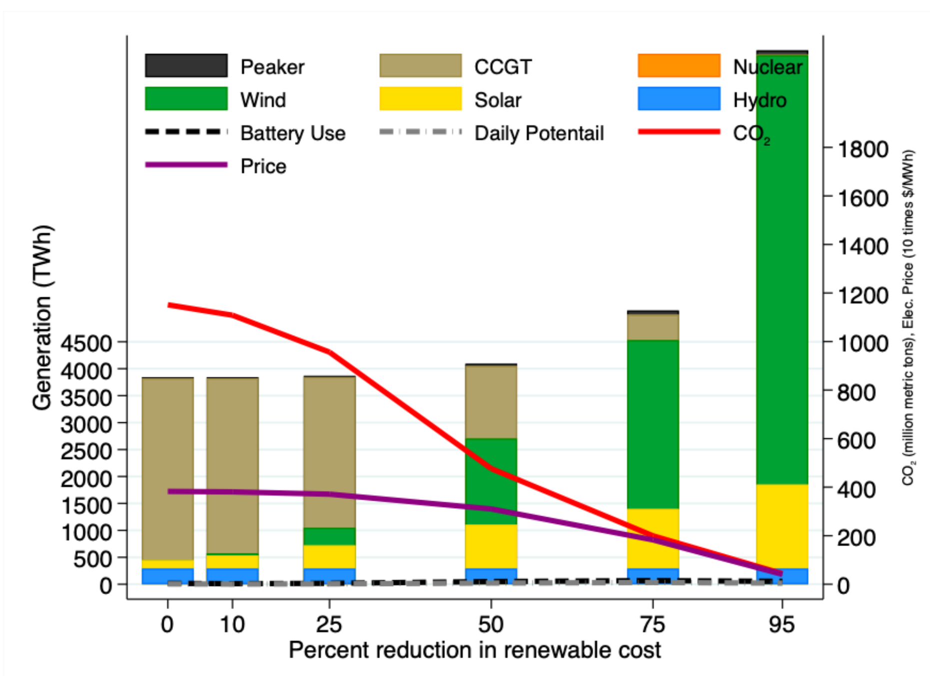


Figure O.A.7: Reduction in renewable generation capital costs (Iso-elastic demand).

Notes: Baseline parameterization with iso-elastic demand aggregated across all regions.

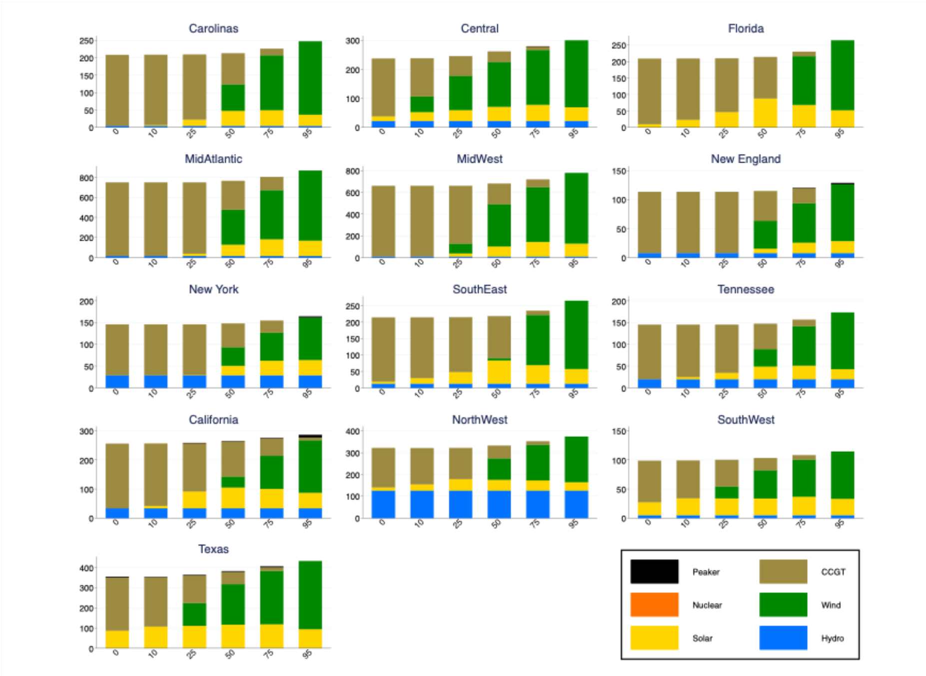


Figure O.A.8: Reduction in renewable generation capital costs for each region

Notes: Baseline parameterization.

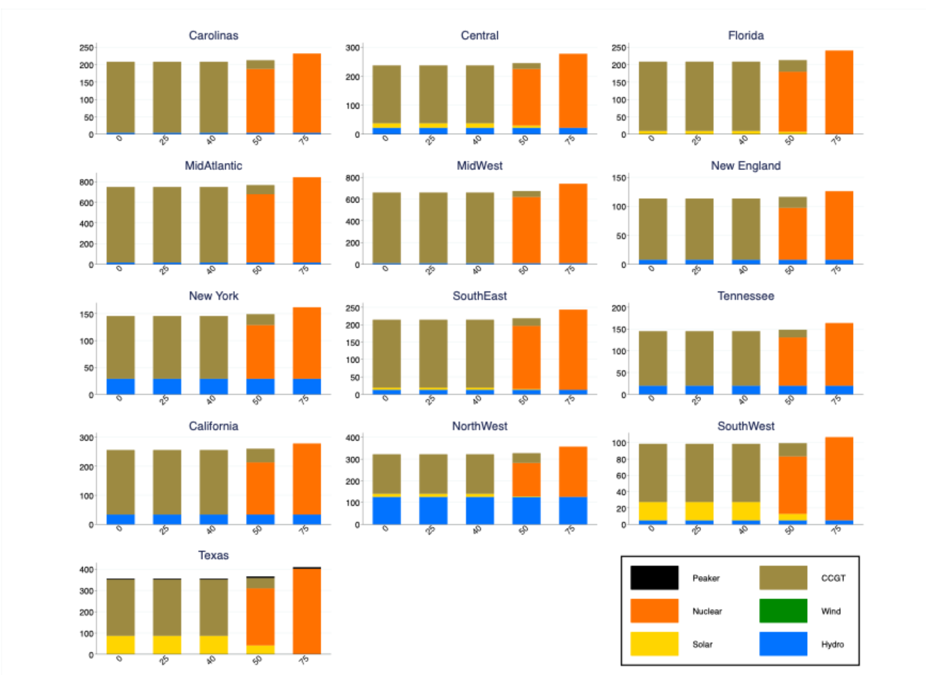


Figure O.A.9: Reduction in nuclear generation capital costs for each region (Linear demand)

Notes: Baseline parameterization.

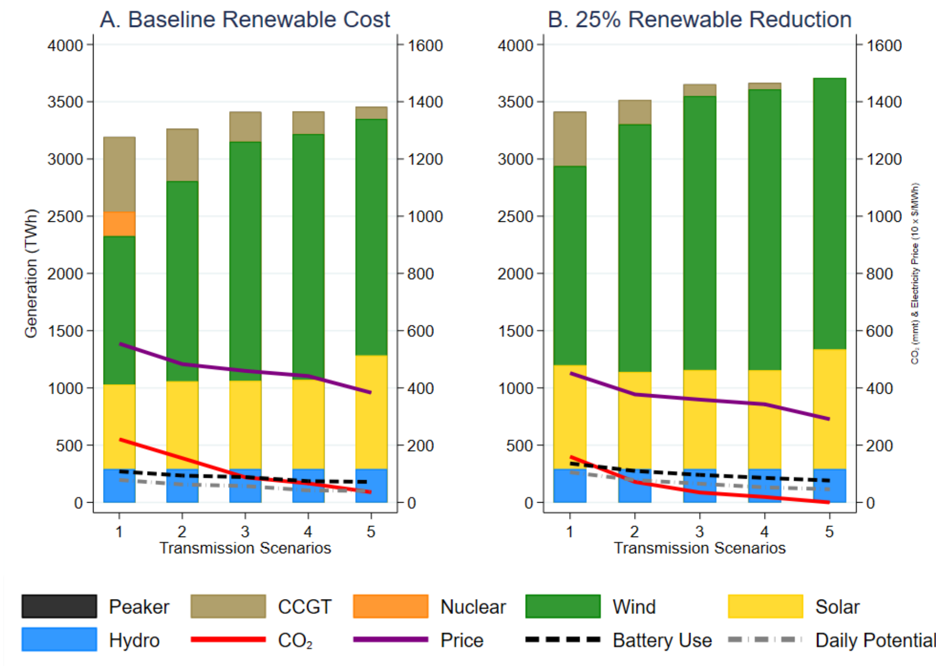


Figure O.A.10: First best transmission scenarios with SCC=100.
Notes: Baseline parameterization. The Baseline (Scenario 1) has 13 distinct transmission regions. Scenario 2 has 5 distinct transmission regions: NE, SE, MW, Texas, and West. Scenario 3 has 3 distinct transmission regions: East, Texas, and West. Scenario 4 has 2 distinct transmission regions: East plus Texas, and West. Scenario 5 has 1 unified transmission region for the whole country.

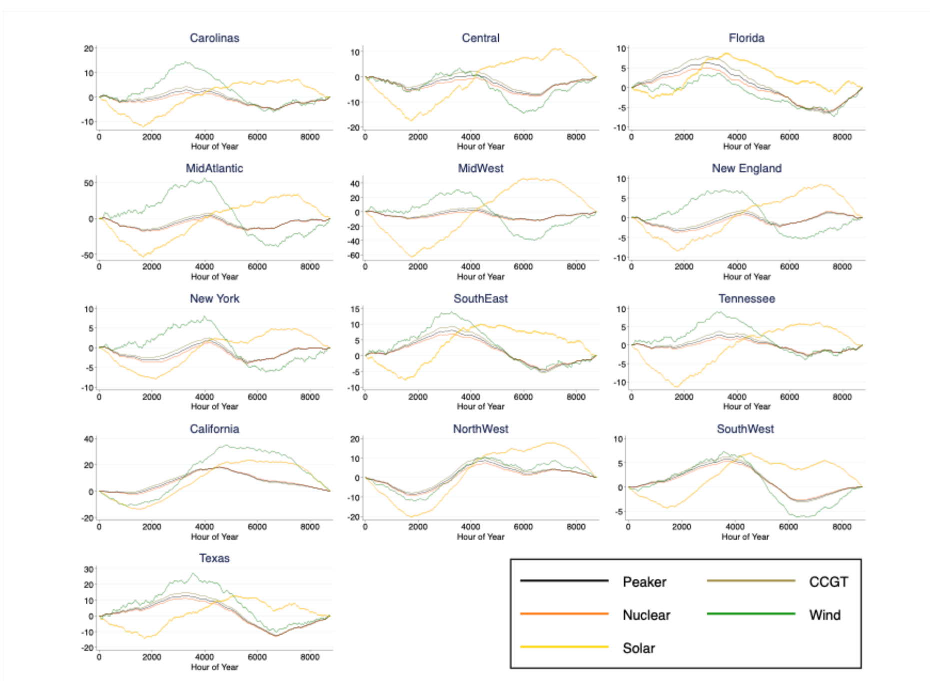


Figure O.A.11: Cumulative battery storage relative to Jan 1 for each region.
Notes: Assumes linear demand, free battery capacity, and a single generation technology. Required battery capacity is the range.

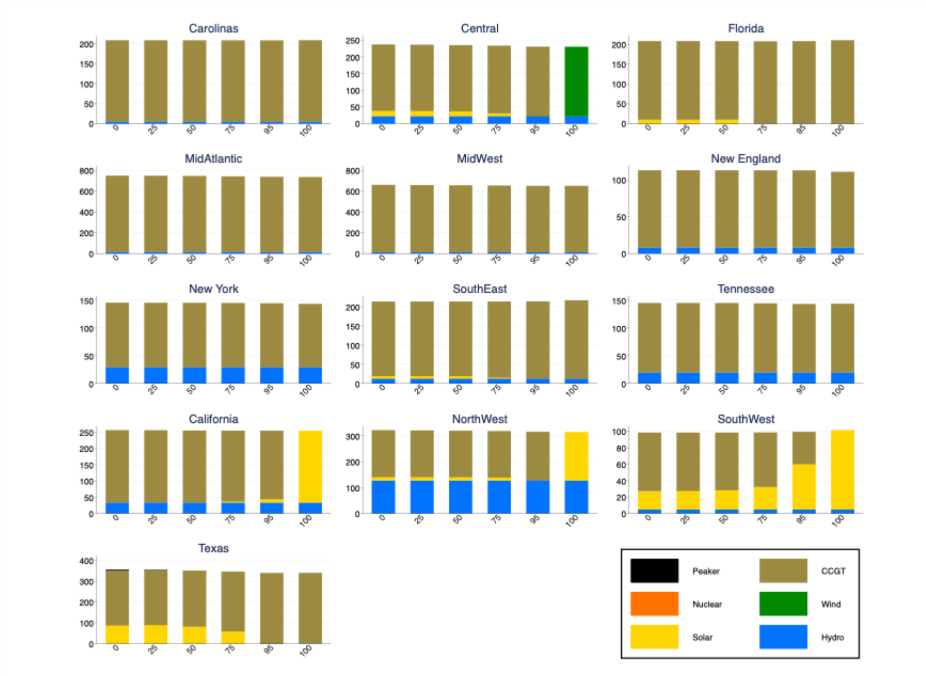


Figure O.A.12: Reduction in battery capital costs for each region

Notes: Baseline parameterization.

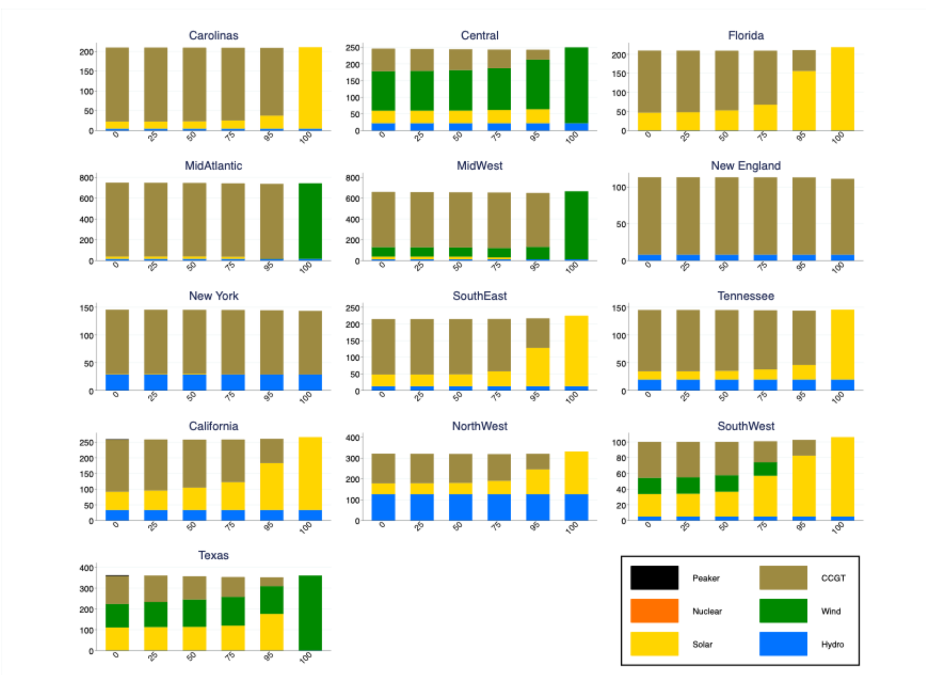


Figure O.A.13: Reduction in battery capital costs for each region (25% renewable capital cost reduction)

Notes: Baseline parameterization and 25% reduction in renewable capital costs.

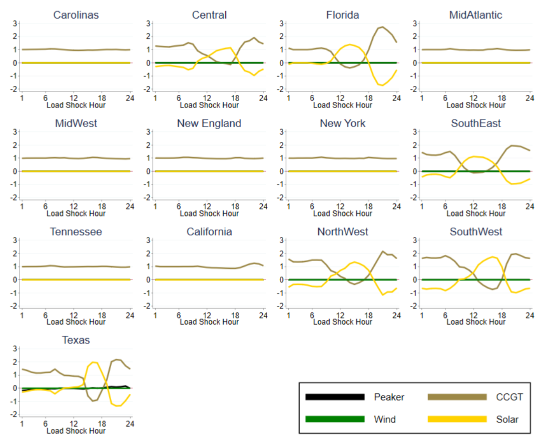


Figure O.A.14: Incremental generation from each technology by hour-of-day load shocks for each EIA region.

Notes: Baseline parameterization. Vertical axis is the change in generation of each technology (MWh/MWh) across all hours from a one percent shock to load in only hour h each day of the year.

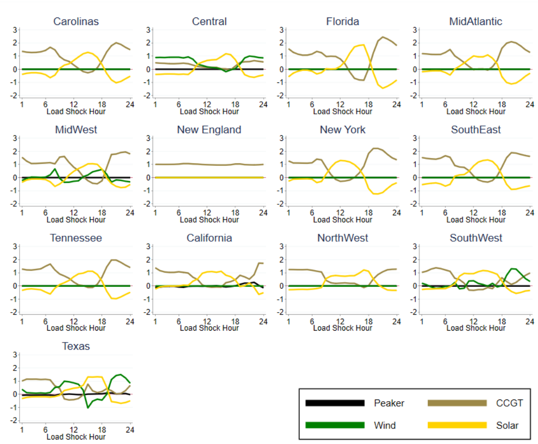


Figure O.A.15: Incremental generation from each technology by hour-of-day load shocks for each EIA region (25% renewable capital cost reduction).

Notes: Baseline parameterization and 25% renewable capital cost reduction. Vertical axis is the change in generation of each technology (MWh/MWh) across all hours from a one percent shock to load in only hour h each day of the year.

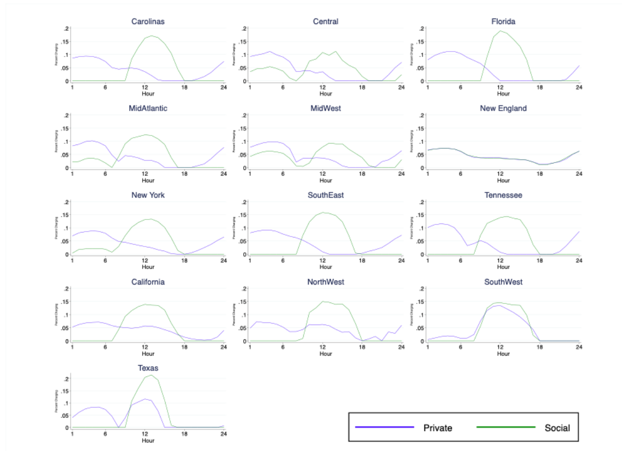


Figure O.A.16: Private and socially optimal EV charging profiles for each region.
Notes: Baseline parameterization. "Private" charging profile optimizes benefits assuming no carbon damages. "Social" charging profile optimizes benefits assuming the SCC is $100 per mt.

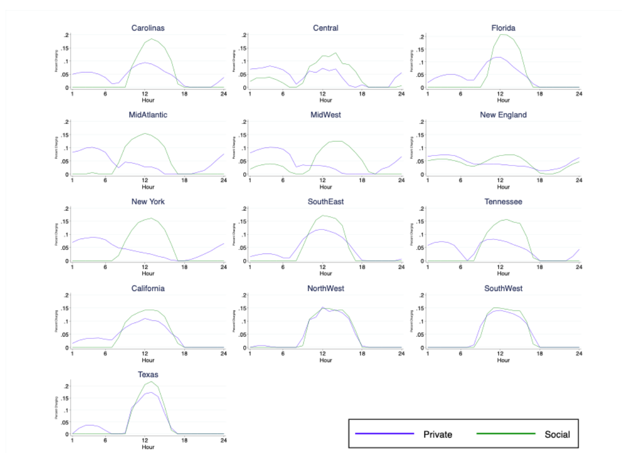


Figure O.A.17: Private and socially optimal EV charging profiles for each region (25% renewable capital cost reduction).
Notes: Baseline parameterization. "Private" charging profile optimizes benefits assuming no carbon damages. "Social" charging profile optimizes benefits assuming the SCC is $100 per mt.

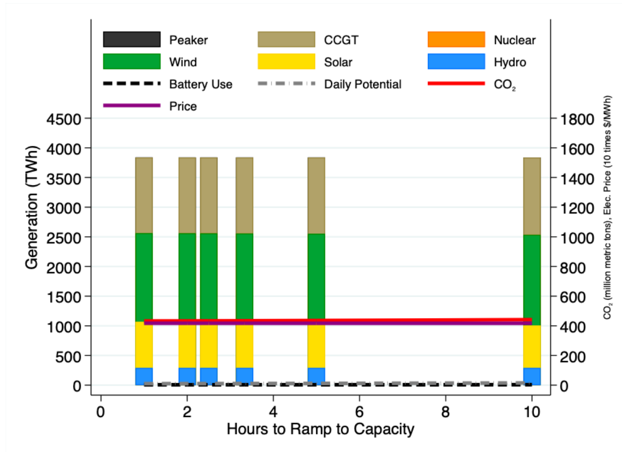
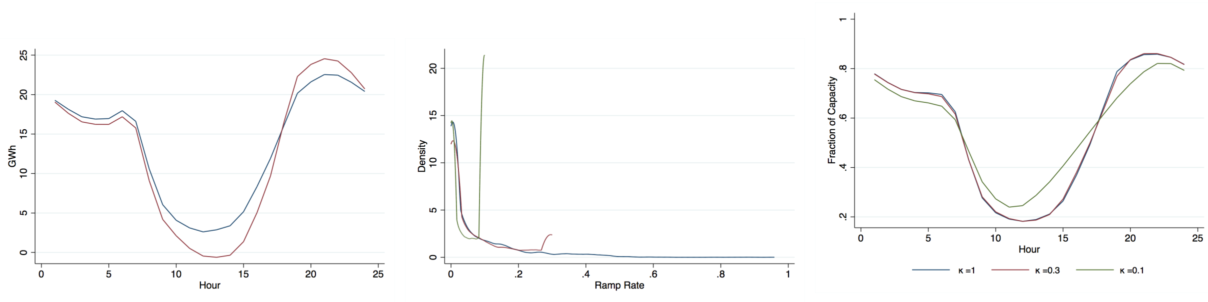


Figure O.A.18: Ramping Constraints

Notes: Baseline parameterization and 50% renewable capital cost reduction. Electricity price is the total cost divided by total production. Hours to ramp capacity is defined as $\frac{1}{\kappa}$, where κ is the parameter in the ramping constraint.



(a) Consumption minus Renewable Generation **(b) Density of Gas Combined Cycle Ramping** **(c) Gas Combined Cycle Generation as a Fraction of Capacity**

Figure O.A.19: Ramping Constraints in California

Notes: Baseline parameterization and 50% renewable capital cost reduction.

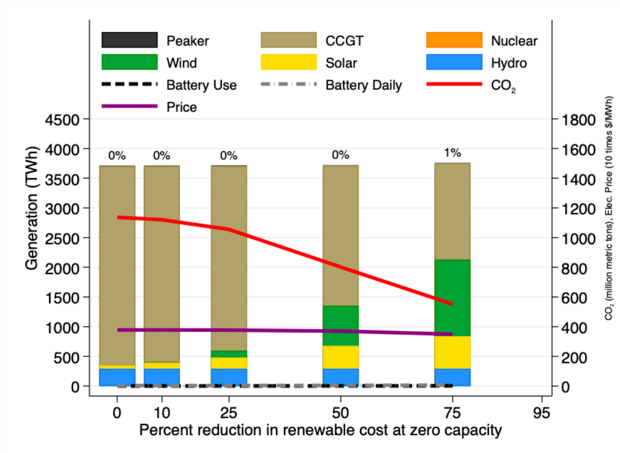


Figure O.A.20: Upward Sloping Renewable Supply

Notes: Baseline parameterization aggregated across all regions. Renewable capacity costs are a quadratic function of capacity rather than linear as in the main text.

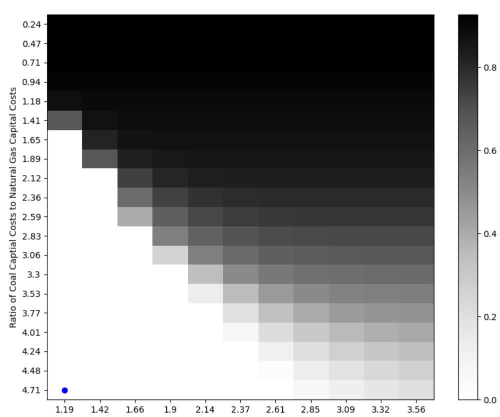


Figure O.A.21: Coal generation sensitivity analysis.

Notes: Grey scale indicates the ratio of coal generation to total generation. Baseline operating cost ratio is 1.19 and baseline capital cost ratio is 4.71, as indicated by the blue dot.