Decarbonization and Electrification in the Long Run*

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Abstract

Decarbonization and electrification will require a transformed electricity grid. Our long-run model of entry and exit of generation and storage capacity captures crucial aspects of the electricity industry such as time-varying demand for electricity, intermittency of renewables, and intertemporal optimization of storage. We derive several theoretical possibilities that differ in surprising ways from short-run intuition: A carbon tax can increase electricity consumption; cheaper storage can decrease renewable capacity; cheaper renewables can increase carbon emissions; and an increase in electricity demand (e.g., electrification) can decrease emissions. We calibrate the model using 2019 hourly data on demand and renewable availability for thirteen regions covering the contiguous U.S. A carbon price of $150 or more essentially eliminates carbon emissions. Given a modest decarbonization goal, a renewable subsidy performs better than a nuclear subsidy, but this ranking is reversed for an ambitious decarbonization goal. Transmission expansion yields large emissions reductions if renewable costs fall sufficiently, but policies promoting storage are unlikely to yield significant benefits. Electrifying 100% of car miles traveled (thereby eliminating gasoline vehicle carbon emissions) increases electricity-sector carbon emissions by 23-27% if vehicles are charged at night, but could *decrease* electricity-sector carbon emissions if vehicles are charged during the day.

JEL Codes: H23, Q4, Q53, Q54

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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. At the same time, 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 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/or electrification, free from the hysteresis of legacy investments and historical accidents.[3] As such, our framework provides a unique perspective on the end goal of policies for the electricity sector and can analyze and quantify the long-run effects of policy.

[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 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) and Palmer et al. (2011).

Our theoretical model is analytically tractable and enables us to derive several long-run possibilities which differ from their short-run analogs.[4] First, although carbon pricing decreases carbon emissions, it can *increase* overall electricity consumption in the long run if it induces sufficient entry of low-cost clean technologies. Second, cheaper storage can increase or decrease long-run 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. Third, a decrease in the cost of renewables may increase carbon emissions if the renewables crowd out a zero-emission technology such as nuclear. 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. These theoretical possibilities illustrate the importance of the long-run perspective in electrification and climate policy.

To quantify the 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 by both its 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 unknown joint distribution of shocks to demand, 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]

Our calibrated model shows the relevance of our theoretical results and provides additional insights into decarbonization policies. Our baseline calibration uses capital cost estimates for the near future, and the vast majority of generation is from natural gas.[6] Carbon pricing reduces long-run carbon emissions by inducing a mixture of renewable and/or

[4] Large multi-sectoral models such as the 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 A.3.

[6] Capital costs, especially for renewables, are highly uncertain, so we consider a broad range of sensitivity analyses and assumptions about technological progress. Coal-fired generation as a legacy technology has no sunk cost advantage in our long-run model. Holland et al. (2020) document the decline in coal-fired

nuclear generation, but, consistent with our theoretical results, does not necessarily reduce electricity consumption. We find substantial benefits from carbon pricing and almost complete decarbonization with a carbon price of $150.

In the absence of carbon pricing, promoting renewable generation may be an alternative way to reduce carbon emissions from the electricity sector. In our baseline, renewable generation is rather modest. But this baseline does not include policies such as subsidies for renewable capacity or technological innovation, both of which can be modeled in our framework as a reduction in renewable capital costs. We calculate that these policies can decarbonize electricity and lead to benefits increases that are sufficient to justify substantial innovation expenditures or potentially to rationalize direct renewable subsidies.[7]

Similar to renewables, nuclear energy can decarbonize electricity without carbon pricing, but only if capital costs are reduced sufficiently: approximately a 50% cost reduction is required in our calibration.[8] If cost reductions exceed this threshold level, then nuclear technology replaces both natural gas and renewables, and electricity is decarbonized almost completely. However, if cost reductions do not meet the threshold, then nuclear technology is not adopted and carbon is not reduced.[9] Comparing the results for nuclear energy to renewables shows that the relative effectiveness of policies to promote one or the other depends on the desired stringency of the decarbonization. Given a modest decarbonization goal, a renewable subsidy performs better than a nuclear subsidy, but this ranking is reversed for an ambitious decarbonization goal.

Adding transmission capacity and electricity storage to the grid can also help decarbonize electricity. Intuitively, transmission and storage would seem to benefit renewable generation by shifting it from low value to high value locations or times.[10] In our calibration, increasing

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. Helm and Mier (2019) present a theoretical model of intermittent renewables. See also Weber and Woerman (2022), Eisenack and Mier (2019), Pommeret and Schubert (2021) and Junge et al. (2022).

[8] Davis and Hausman (2016) study the effects of nuclear power plant closure.

[9] 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.

[10] 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

transmission capacity does not generate benefits of any significant magnitude unless there are complementary policies that reduce costs of renewable generation. In that case, transmission can lead to substantial decarbonization by increasing renewable investment in regions with better renewable potential. We find the largest benefit from transmission connecting wind resources in the Midwest with demand in the East. Storage does not generate benefits of any significant magnitude even with complementary policies that reduce costs of renewable generation unless batteries become almost free and sufficient battery storage is constructed to allow interseasonal storage.[11] In addition, somewhat counterintuitively, we find that a decrease in the cost of storage may lead to a *decrease* in renewables in some regions because storage favors the technology with the lowest long-run average cost (adjusted for availability). These results imply that policies promoting only transmission or only storage are unlikely to yield significant benefits.

Our framework allows a comprehensive welfare analysis of second-best subsidies in the absence of carbon pricing.[12] Importantly, we can assess complementarities between subsidies for batteries and for renewables. Battery subsidies are complementary to other subsidies, but the welfare gains from second-best battery subsidies are modest. Consistent with our earlier results, we find the largest welfare gains from subsidizing renewables and batteries if the Social Cost of CO_2 (SCC) is low, but from subsidizing renewables and nuclear if the SCC is high.

Our last long-run effects analyze increases in demand resulting from policies that encourage electrification. Consistent with our theoretical results, electrification may help or hinder decarbonization by affecting renewable capacity. In our baseline, load shocks in most hours and locations simply increase natural gas capacity and the long-run incremental emissions are approximately the natural gas power plant emissions rate. However, with lower renewable costs, we find some load shocks can increase solar capacity so that the incremental emissions can be zero or even negative in some hours and regions.[13]

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has been widely studied but is computationally intensive so most studies focus on a single region. See Karaduman (2020), Butters et al. (2021), and Shrader et al. (2021).

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

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

[13] 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

The hourly variation in incremental emissions implies that the effects of large scale electrification depends on the hours at which the electricity is used.[14] For transportation, this means the hours the electric vehicle (EV) is 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.[15] However, with a different charging profile, EV charging can result in very low incremental emissions. Remarkably, if renewable costs are lower, a charging profile in which charging occurs exclusively in mid-day has *negative* incremental 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 a dramatic entry of renewables. The socially optimal charging profile balances emissions reductions with private surplus losses and has positive but modest incremental emissions.

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

grid dispatch models (Raichur et al. (2015)). Hawkes (2014) estimates long-run marginal emissions using a dispatch model of the British electricity grid. 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.

[14] Many studies analyze the effects of the timing of electrification and efficiency in the short run. See for example Boomhower and Davis (2020).

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

incentives created by the policies. Our analysis offers a novel perspective on a rich set of transformative technologies 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 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 $U_t'' < 0$. Define also the demand function, D_t, as the inverse function of U_t' defined by $U_t'(D_t(p)) \equiv p$.

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

[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. We address these assumptions in the Online Appendix A.1.

$Q_t + b_t \leq \sum_i q_{it}$, 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 (16) as:

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

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

$$Q_t \geq 0 \qquad d\mathcal{L}/dQ_t = U_t'(Q_t) - p_t \leq 0 \qquad \forall t \qquad C.S. \tag{3}$$

$$q_{it} \geq 0 \qquad d\mathcal{L}/dq_{it} = -c_i + p_t - \lambda_{it} \leq 0 \qquad \forall i, t \qquad C.S. \tag{4}$$

$$d\mathcal{L}/db_t = -p_t + \phi_t = 0 \qquad \forall t \tag{5}$$

$$S_t \geq 0 \qquad d\mathcal{L}/dS_t = \phi_{t+1} - \phi_t - \mu_t \leq 0 \qquad \forall t \qquad C.S. \tag{6}$$

$$K_i \geq 0 \qquad d\mathcal{L}/dK_i = \sum_t \lambda_{it} f_{it} - r_i \leq 0 \qquad \forall i \qquad C.S. \tag{7}$$

$$\bar{S} \geq 0 \qquad d\mathcal{L}/d\bar{S} = \sum_t \mu_t - r_s \leq 0 \qquad C.S., \tag{8}$$

[18] There are $(3 + I)T + I + 1$ choice variables. Hourly periods over a year (8760 hours) and four technologies imply over 60,000 choice variables.

[19] H_t is not technically the Hamiltonian of (16) because it treats the adjoint variable differently.

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 marginal cost must be generating at 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 $p_t = \min_i\{\max\{c_i, U_t'(\sum_{i'\leq i} f_{i't}K_{i'} - b_t)\}\}$.*

This lemma is illustrated graphically in Figure 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 $d\mathcal{L}/d\bar{S} = \sum_t -p_t b_t/\bar{S} - r_s$.

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

The derivatives in Proposition 1 are simply profit per unit capacity. They create a gradient, which is used in our numerical simulation to find the optimal capacities. 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 [16], may not be efficient because of the external costs from carbon emissions. Accordingly, we define *private surplus* as the optimized value of [16] 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 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. Letting τ denote the carbon tax and 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., $\Delta \sum_t Q_t \lessgtr 0$.*

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.

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]

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

Result 2. *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 $K_i = \frac{\sum_t D_t(\bar{p})}{\sum_t f_{it}}$.

Although it may seem intuitive that battery storage may result in more renewables, Result 2 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, 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.

Our next result relates the capital cost of renewable generation and emissions.

Result 3. *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 marginal cost zero emission technology such as nuclear and an increase in the capacity of a polluting technology.

Another interesting difference in the short-run 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 price effects crowd out other

[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.

electricity uses or if 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 also has price effects. Prices face upward pressure in periods with demand increases but downward pressure in periods with additional capacity. Thus, the long-run change in overall electricity usage may be greater or less than one-for-one with electrification.

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.[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. The electricity regions are shown in Figure A.2. The East interconnection consists of nine EIA regions: Carolinas, Central, Florida, MidAtlantic, MidWest, New England, New York, SouthEast, and Tennesee. The West interconnection consists of three EIA regions: California, NorthWest, and SouthWest. The Texas interconnection is a single EIA region. We initially consider each EIA region to be independent to capture geo-

[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 was abnormal due to the COVID-19 pandemic.

graphic variation in load and renewable availability, but we later combine them to capture the benefits of increasing transmission capacity between them.

3.1 Model calibration

Our model calibration requires us to parameterize hourly demand for our thirteen electricity regions, estimate capital and marginal costs for our five generation technologies, estimate capital costs for storage, and estimate hourly availability for solar and wind in each of the thirteen regions.

3.1.1 Demand

Modeling hourly demand in each electricity region requires both assumptions about functional forms and data on observed prices and quantities. We assume demand in each hour is independent of demand in other hours and assume either a linear or iso-elastic functional form.[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] 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 demand is collected from the EIA 930 and is the total of electricity load from all reporting entities within the EIA region for that hour. The mean observed demand by season and hour of day is shown in Figure 1 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 (Carolinas, Florida, NorthWest, SouthEast, SouthWest, and Tennesee), we used the FERC 714 data on

[25] Linear demand allows for the possibility of curtailed renewable generation while iso-elastic demand serves as a robustness check and facilitates adding demand curves across interconnecting electricity regions.

[26] For linear demand, $D(p) = A - Bp$, the two parameters are $B = 0.15Q_0/P_0$ and $A = 1.15Q_0$ where P_0 and Q_0 are the observed price and demand. For iso-elastic demand $D(p) = Ap^{-\epsilon}$ the two parameters are $\epsilon = 0.15$ and $A = Q_0/P_0^{-\epsilon}$, and we assume a finite choke price so that the consumer surplus integral converges.

system lambdas for our observed prices. The mean hourly price is shown in Figure A.3 and summary statistics are in Table A.1. The observed demands and prices show substantial variation across hours, seasons, and regions which we assume is representative of underlying structural demand conditions.

3.1.2 Capital and marginal costs

We consider five generation technologies: solar, wind, nuclear, combined cycle gas, and combustion turbine (peaker) gas. The latter three are dispatchable, and the latter two use natural gas and consequently generate carbon emissions. Combustion turbine (peaker) gas plants have low capital costs but high marginal costs, and hence are used primarily when electricity prices are high. Combined cycle gas plants have high capital costs but low marginal costs, and are used for more hours.[27] Our other three technologies have no carbon emissions. Advanced nuclear has very low marginal costs but very high capital costs. Solar and wind power both have zero marginal cost and intermediate capital costs. If they were dispatchable, these technologies would dominate advanced nuclear. Because of intermittency, the equilibrium may have positive capacities of nuclear as well as renewables.

Our baseline capital and marginal costs for the five generation technologies and for grid-scale battery storage represent capacity entering service in 2026. (See Table 1.) 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. Marginal cost, c_i, is the levelized variable cost and is primarily fuel costs for the natural gas technologies.

The capital costs are forward looking and highly speculative. Table A.2 shows how capital and marginal costs changed from 2014 to 2021. Over this time frame, capital costs declined dramatically, especially for renewables: 76% for solar and 54% for wind, while advanced nuclear capital costs declined the least. Capital costs are projected to continue to fall. Table A.3 shows projections to 2050 for capital costs which shows large declines for solar and for battery storage. Because of the speculative nature of these distant forecasts,

[27] We do not consider coal technologies. Ignoring environmental costs, coal technologies are almost dominated by our combined cycle gas technology. Incorporating environmental costs from local pollution make it unlikely that coal would be a desirable technology.

our baseline focuses on 2026 costs, and we consider sensitivity analysis to a wide range of assumptions.

3.1.3 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. Unfortunately, renewable capacity, which is required to calculate our capacity factors, is not reported in the EIA 930 and is increasing rapidly throughout 2019. 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 2 shows mean hourly capacity factors by season and hour of day for each region, and summary statistics are in Table A.1. The capacity factors show seasonal and hourly patterns which are consistent with estimates of renewable availability.

3.2 Solution algorithms

We use two different approaches to solve the planner's problem. The first approach directly solves the planner's problem using a publicly available quadratic programming solver.[29] This approach finds the solution relatively quickly, but can only be used when the benefit function is quadratic and suffers from the curse of dimensionality, particularly for cases in which the regions are combined.

The second approach uses the theoretical results to dramatically reduce the dimensionality of the choice vector and then use a gradient search algorithm to optimize capacity for

[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 Online Appendix A.2 for details.

[29]The particular solver 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.

each technology.[30] Without a storage technology, it is relatively 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 annual profit for each technology, which Proposition 1 shows can be used to construct a gradient vector. From here, a standard gradient search optimization is computationally efficient.[31] 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 [16]. Then it is a matter of finding the feasible vector of net charges that maximizes this sum. We do this by employing a dynamic programming algorithm in which 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 Proposition 1 shows can be used to construct the gradient vector including storage. 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. Overall, this second approach is slower than the quadratic programming approach, but can be applied to more general benefit functions and performs well even when the regions are combined.

4 Decarbonization Results

From a baseline of no electricity storage and separate EIA regions, we begin by calculating the benefits of carbon pricing, of reducing renewable and nuclear generation capital costs, and of expanding transmission and battery storage. Then we analyze interactions between various policies and determine second best policies in lieu of carbon pricing.

[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 marginal costs, and with intermittent technologies, such a ranking is meaningless.

[31] We use the method described in Barzilai and Borwein (1988) to select the step size in each iteration.

4.1 Carbon pricing

Without carbon pricing, our baseline calibration of the long-run equilibrium has CO_2 emissions of 1,107 million metric tons (mmt) per year (Table 2).[32] This is 30% lower than actual 2019 CO_2 emissions of 1604 mmt (Holland et al. (2022)). This difference arises because there is no modeled coal generation (whereas coal accounted for 25% of actual 2019 electricity generation) and because modeled electricity consumption is slightly lower than actual: 3716 TWh instead of 4000 TWh due to a higher modeled electricity price (the weighted average modeled price is $38 per MWh while the actual 2019 price is $27 per MWh).[33] Our baseline long-run equilibrium shows that optimally building the electricity grid using current technologies could reduce carbon emissions substantially even in the absence of carbon pricing.

Carbon pricing would reduce long-run carbon emissions further (Table 2 and Figure 3). Relative to our baseline, a carbon tax of $50 per ton of CO_2 reduces long-run carbon emissions by 50% and a $150 tax eliminates over 90% of carbon emissions from the electricity sector.[34] The emissions reductions are accomplished in part by increases in the electricity price. The electricity price increases from the baseline price of $38 per MWh to $56 per MWh with a $200 carbon tax.[35] Total electricity consumption can increase or decrease as shown in Result 1. With linear demand, the carbon tax reduces annual electricity consumption: from 3716 TWh to 3190 TWh (15%) for a $200 carbon tax. However, with iso-elastic demand, the relationship is not monotonic: increasing the carbon tax first decreases then increases electricity consumption, and the $200 carbon tax only decreases electricity consumption less than 1%. (See Panel B of Figure 3.) In the long run, carbon pricing can decarbonize electricity without substantial decreases in electricity consumption or excessive increases in electricity prices.

[32] With iso-elastic demand, CO_2 emissions are 1,153 mmt. See Table A.4. We use metric tons throughout.

[33] 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.

[34] The carbon tax required for deep decarbonization is higher than that calculated by Stock and Stuart (2021). The importance of our rich set of representative time periods in our model is explored further in Online Appendix A.3.

[35] With iso-elastic demand, the electricity price rises from $38 to $60. See Table A.4.

Decarbonization under carbon pricing arises mainly from the change in long-run mix of generation technologies. In the baseline, natural gas plants account for 88% of total generation (Figure 3). At carbon prices above $50 per ton, natural gas accounts for less than half of total generation and is gradually eliminated at higher carbon prices. At carbon prices above $100 per ton, installing nuclear capacity is optimal. Because nuclear capacity is dispatchable and has low marginal cost, nuclear capacity displaces both renewable and gas capacity, 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 (see Figure 4). 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 despite availability of solar because solar energy cannot generate electricity at night.

Whether carbon pricing is socially beneficial depends on damages from carbon emissions (i.e., the social cost of CO_2, SCC). Because the SCC is highly uncertain, Table 2 presents the annual welfare gains for a wide range of SCC's ranging from $0 to $200 per ton of CO_2.[36] If the SCC is $0, then carbon pricing is purely distortionary, the lost private surplus exceeds the carbon tax revenue, and carbon pricing has negative welfare gains. For a positive SCC, the gains from carbon tax revenue and reduced damages may exceed the lost private surplus. For any carbon price, annual welfare gains increase with higher SCCs. For any SCC, annual welfare gains increase until the carbon price is equal to the SCC (the Pigouvian price) and then decrease thereafter. The benefits of carbon pricing can be substantial. If the SCC is $100, then the Pigouvian carbon price leads to $47 billion in annual welfare gains. To put this number in perspective, it is approximately 33% of the total revenue from electricity generation in our baseline.

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. If capital costs fall due to technological advances, then market participants would optimally install the cheaper technology. Even without technological ad-

[36] Table A.4 presents the benefits for iso-elastic demand.

vances, public policies, such as capital subsidies, can encourage installation of renewables or nuclear power.

Lower capital costs of solar and wind can reduce carbon emissions quite dramatically. (See Figure 5 and Table A.5.) A 25% reduction in renewable capital costs reduces carbon emissions by 18%; a 75% reduction in costs reduces carbon emissions by 85%; 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 gas peaker capacity for use in the few hours in which wind or solar are not available.[37]

Because renewables are not dispatchable, a substitution from natural gas to renewables leads to an increase in total capacity. With a 95% renewable cost reduction, total capacity is six times higher than baseline with 0.8 million MW of solar and 2.8 million MW of wind capacity.[38] However, increases in renewable generation are not proportional to increases in capacity two reasons. First, renewable generation is increasingly installed in regions with lower capacity factors.[39] Second, substantial renewable generation is curtailed with linear demand. If renewable capital costs are 50% lower, then about four percent of renewable generation is curtailed. (See Figure 5.) Even lower costs leads to dramatic curtailment: if costs are 95% below baseline, then 57% of renewable generation is curtailed.[40] This substantial curtailment is optimal because the renewable generation is very inexpensive and is profitable in enough hours to cover its capital costs.

[37] The generation by region is shown in Figure A.7.

[38] 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.

[39] 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.

[40] Table A.6 and Figure A.6 show the case of iso-elastic demand in which, by assumption, no load is curtailed.

Next we quantify the benefits of a reduction in renewable capital costs.[41] If renewable costs fall due to some breakthrough technology, then society benefits because electricity prices fall and electricity consumption increases. Thus even without accounting for climate damages, a 75% cost reduction in renewables results in $57 billion annual benefits. (See Table A.5.) With climate damages, the benefits are even greater: $105 billion to $246 billion per year depending on the SCC. These benefits show substantial returns to research and development spending that reduces the cost of renewables. Even if renewable capital costs do not fall, public policy can still encourage renewable adoption for example by subsidizing private capital costs.[42] Without climate damages, renewable subsidies are purely distortionary, and subsidy costs exceed the benefits. (See Table A.5.) However, with positive climate damages, subsidizing renewable capital costs may be beneficial. For example, a subsidy reducing private renewable capital costs by 75% would cost $146 billion but would yield benefits of over $150 billion if the SCC exceeds $100 per ton.

Decarbonization can also result from installing nuclear capacity, but only if its capital costs fall sufficiently. Figure 6 and Table A.7 show nuclear capacity is zero unless capital costs fall by 50% or more. However, once this threshold is reached, nuclear power becomes the dominant power source and replaces both renewables and natural gas generation. At a 50% reduction in nuclear capital costs, nuclear power generates 78% of electricity and benefits exceed $100 billion for values of the SCC that are greater than $100.[43] These benefits are sufficient to offset the subsidy cost of $89 billion required to reduce private nuclear capital costs by 50%. Thus, nuclear capacity can decarbonize electricity, but it requires substantial cost reductions and crowds out other power sources, including renewables.

From a cost-effectiveness perspective, renewable subsidies are more cost effective for modest carbon reductions, *e.g.,* CO_2 emissions above ~165 mmt, because a nuclear subsidy is ineffective. For a CO_2 emissions target of ~165 mmt, the nuclear subsidy is more cost effective. To see this, notice the abatement cost of reducing emissions to ~165 mmt is equal to the benefits with a zero SCC minus the cost of the subsidy. The nuclear subsidy has

[41] Benefits are defined as the change in the sum of private surplus and damages from carbon emissions evaluated at the SCC.

[42] A capital cost subsidy must ensure that capacity factors are not distorted. Capacity factors are exogenous in our model.

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

abatement costs of \$80.8 billion (=8.4-89.2) and the equivalent renewable subsidy has higher abatement costs of \$89.1 billion (=57.3-146.4).[44] The nuclear subsidy is also more cost effective for an even more aggressive CO_2 emissions target of ~10 mmt.

4.3 Expanding transmission and battery storage

Transmission and battery capacity can make intermittent renewables more valuable by shifting renewable electricity from low value to high value locations or times. The benefits of these shifts will depend on renewable availability, so we analyze increasing transmission and battery capacity both in our baseline and in scenarios with higher renewable penetration.

Our baseline assumes no transmission constraints (i.e., a single hourly electricity price) within each EIA region but no electricity transmission between regions. To model increasing transmission capacity, we combine load and dispatchable capacity across EIA regions but retain renewable capacity for each EIA region to capture temporal and spatial variation in renewable availability.[45] For example, if we combine two EIA regions into a single region then we have 7 different generation technologies: the three dispatchable technologies, two wind technologies, and two solar technologies. 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.[46]

Carbon emissions reductions and benefits from transmission capacity expansion are relatively small in our baseline (See Figure 7 and Panel A of Table A.8). With full interconnection (Scenario 5), carbon emissions are reduced only 15% from baseline and benefits are \$7 billion to \$38 billion depending on the SCC. The largest gain in benefits is between Scenarios 4 and 5 which interconnect the East/Texas and West and results in additional solar and wind generation.

[44]For comparison, the minimum abatement cost of achieving emissions of ~165 mmt can be attained by a carbon tax. Using linear interpolation with the results in Table 2 shows that a carbon tax of approximately ~ \$125 would yield CO_2 emissions of ~166 mmt at an abatement cost of ~\$49 billion, which is about half the abatement cost of the inefficient policies.

[45]This procedure follows Cicala (2022). Essentially, we are assuming 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.

[46]Scenario 5 requires capacity optimization for 29 different technologies: three dispatchable technologies, 13 wind technologies, and 13 solar technologies.

Benefits of transmission are more substantial with higher renewable penetration. Assuming a 25% reduction in renewable capital costs, additional transmission capacity decreases carbon emissions substantially. Interconnecting the East (Scenario 3) decreases carbon emissions by 50% relative to Scenario 1 (Figure 7 and Panel B of Table A.8). Full interconnection (Scenario 5) would reduce carbon emissions by 62% relative to Scenario 1 and generate over $100 billion in benefits if the SCC exceeds $100. These benefits, which would need to be compared with the costs of transmission capacity expansion, shows the advantage of allowing electricity to move from low to high value locations.[47]

Moving electricity from low to high value times requires electricity storage. To see whether storage increases renewable capacity, we present results for a variety of battery capital costs in conjunction with baseline and reduced renewable capital costs (Figure 8 and Table A.10).[48]

Four results stand out. First, the results for the model with storage at baseline costs offer only modest benefits relative to the model without storage, regardless of the renewable costs. Second, decreases in battery costs give higher benefits if renewable costs decrease. In Panel A of Table A.10, differences in emissions, benefits, and renewable capacity are small except for the case in which batteries become completely free. In Panel B, reductions in battery costs lead to decreases in emissions and increases in benefits, but little differences in renewable capacity (except when batteries are free). Third, if battery capacity is completely free, the optimal battery capacity is enormous. Figure A.10 shows the cumulative battery storage required in each region to generate all electricity from a single technology. The interseasonal storage requires exceptionally large battery capacity which is only optimal if batteries are costless and never justifies the required subsidies.[49] Fourth, as discussed in Result 3 in the theory section, costless batteries may not lead to any renewable capacity: at baseline renewable costs, generation is exclusively from natural gas in most regions.[50] Overall our

[47]Figure A.9 show the first best transmission capacity expansion, assuming a SCC of $100.

[48]Following Result 2, only the technology with the lowest levelized cost would be constructed if battery costs fall 100%, i.e., are costless. These levelized costs and required capacities are shown in Table A.9.

[49]Battery utilization can be measured by $0.5 * \sum_t |b_t|/\bar{S}$, which can be interpreted as the number of times the average battery is fully charged and discharged per year. For the free battery, this statistic is approximately six indicating very low utilization of the batteries.

[50]The generation by region is shown in Figure A.11 for baseline renewable costs and Figure A.12 for 25% reduction in renewable costs.

calculations show the benefits of batteries are modest unless technological innovation can make batteries costless.

4.4 Policy Interactions and Second Best

In our model, the only policy required to obtain the first-best outcome is the Pigouvian carbon tax. In practice, such a policy is unlikely to be implemented due to a variety of political, institutional, equity, and informational constraints. Instead, jurisdictions may have multiple concurrent policies, such as a modest carbon tax coupled with renewable subsidies.

Table 3 illustrates policy interactions between carbon taxes and renewable subsidies assuming the SCC is $100. In this case, the first best policy is the Pigouvian carbon tax of $100 which yields welfare gains of $46.7 billion. With this carbon tax, any renewable subsidy is purely distortionary and would reduce welfare. If however, the carbon tax is not Pigouvian, then a renewable subsidy can increase welfare. For example, if the carbon tax is only $50, then a renewable subsidy of 25 percent is second best and yields welfare that is only about 6 percent worse than first best.[51] Conversely, in the presence of a renewable subsidy, the second-best carbon tax may be less than Pigouvian. If a carbon tax is feasible, then the optimal policy combination is simply the Pigouvian carbon tax. However, if a carbon tax is not feasible, then the second-best policy combination may require complementary policies.

Assuming a carbon tax is infeasible, Table 4 shows second-best single policies and the relative welfare gains of policy combinations.[52] Panel B presents the welfare gains from each second-best policy in isolation for different SCCs. The second-best renewable subsidy achieves higher welfare gains than either a second-best solar or wind subsidy alone and can attain a substantial proportion of the first-best welfare gains. For a SCC of $200, the second-best nuclear subsidy attains even higher welfare than the second-best renewable subsidy. Combined with our earlier results, we see that from both second-best and cost-effectiveness perspectives, the renewable subsidy is better for modest decarbonization, but the nuclear subsidy is better for more ambitious decarbonization. In contrast to both renewable and

[51] A subsidy of x% means a subsidy which reduces the capital cost of the technology by x% relative to the baseline.

[52] More detail on the results presented in Table 4 are presented in Tables A.10 through A.16.

nuclear subsidies, second-best battery subsidies alone are quite ineffective and yield virtually no welfare gains.

We say two policies are *complementary* if the welfare when the policies are optimized jointly is greater than the maximum of welfare when the policies are optimized in isolation. Panel B of Table 4 presents the welfare gains of second-best policy combinations relative to the maximum of either policy alone.[53] Batteries are touted as complementary to renewables, and indeed, we find positive but modest welfare gains to battery subsidies combined with renewable subsidies. Welfare gains are largest for battery and solar subsidies, but even these complementary policies have lower welfare than the second-best wind subsidy. These gains are modest despite the facts that wind is not correlated with demand and solar power is not available at night. Interestingly, solar and wind subsidies exhibit a symmetric complementarity: The second-best subsidies are each 50%.[54] This symmetry is likely due to correlations between wind and solar capacity factors and demand. To further illustrate, Figure A.13 shows the level sets for welfare as a function of the subsidies for wind and solar. The level sets show that welfare increases most by increasing wind and solar subsidies together. Figure A.14 shows a different pattern for renewable and nuclear subsidies. Although the second-best combined policy subsidizes both renewables and nuclear, almost all the welfare gains can be achieved by subsidizing only renewables.

The policy interactions also can illustrate the possibilities described in Result 3 for carbon emissions. Figure A.15a shows level sets for carbon emissions with wind and solar capital cost subsidies. The iso-emissions lines illustrate that increasing one of the subsidies decreases (or holds constant) carbon emissions. In contrast, in Figure A.15b an increase in the renewable subsidy *increases* carbon emissions for the nuclear subsidy of 50%.

[53]More formally, let W_A be the second-best welfare attained by policy A when policy B is zero; let W_B be the second-best welfare attained by policy B when policy A is zero; and let W_{AB} be the second-best welfare attained by combining policy A and policy B. Panel C of Table 4 shows $W_{AB} - \max\{W_A, W_B\}$.

[54]Across a finer grid of subsidy values, the second-best subsidies are 48% and 49% instead of 50% and 50%.

5 Electrification Results

A decarbonized economy 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 increments to load and then model large scale electric vehicle (EV) adoption. In both cases we consider baseline costs well as lower renewable capital costs.

Electrification has different temporal and locational effects. For each hour and region, we consider a one percent electricity load shock and determine the resulting long-run changes in emissions, total generation, and renewable generation.[55] The results are shown in Figure 9, Figure A.16, and Figure A.17, respectively. In the baseline parameterization, there are seven regions for which a load shock in any hour 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).[56] In other regions, the long-run effects depend on the hour of the load shock. In Central, Florida, SouthEast, NorthWest, SouthWest, and Texas, a load shock at night leads to an increase in natural gas generation, but a load shock during the day leads to an increase in solar generation. In some regions, *e.g.,* SouthWest and Texas, the increase in solar generation may more than offset the load shock, decrease natural gas generation, and lead to negative incremental emissions. Note also that load shocks in other hours of the day may lead to an increase in natural gas generation which is more than equivalent to the load shock and thus reduces solar generation. In these hours, long-run incremental emissions exceed the natural gas emissions rate, *e.g.,* for some night and/or early morning hours in Central, Florida, NorthWest, SouthWest, and Texas.

A 25% reduction in renewable capital costs generally lowers incremental emissions. Mid-day incremental emissions are zero or negative in all regions except New England. In regions with substantial wind availability: *e.g.,* Central and Texas, the incremental emissions may

[55] The load shock is simply a parallel shift of our linear demand for that hour of day on each day of the year.

[56] The seven regions are Carolinas, MidAtlantic, MidWest, New England, New York, Tennessee, and California.

be zero or negative in many more hours of the day. In Central, incremental emissions are very low in all hours of the day, and in Texas, the lower renewable capital costs shift the hours with zero or negative incremental emissions from the mid-afternoon to late morning due to higher wind generation. (Figure A.17). These incremental emissions illustrate the locational and temporal differences in the effects of electrification.

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.[57] Annual EV electricity demand for each EIA region is then spread across hours assuming a charging profile. We first consider a Convenience charging profile from EPRI which assumes EVs are charged primarily at night and a Carbon Minimizing profile which charges primarily in the afternoon.[58]

Table 5 shows the effects of 50% or 100% EV adoption. For the Convenience charging profile, using EVs for 50% of light-duty VMT would increase carbon emissions from electricity by 12% or 130 mmt. Using EV's for 100% of VMT (entirely eliminating gasoline-powered vehicles and their carbon emissions) would only increase carbon emissions from electricity by 23% or 254 mmt. If we normalize by the EV electricity demand, the incremental emissions, generation, and renewable generation show that the incremental 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 profile, 100% EV adoption only increases electricity sector emissions by 7% or 76 mmt. This profile has smaller incremental 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 5), the difference between the profiles is even starker. The Convenience profile has incremental emissions approximately that of natural gas and reduces renewable generation. However, the Carbon Minimizing

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

[58]This charging profile, which is loosely based on the incremental emissions in Figure 9, has 20% of the charging in hours 12, 13, and 14, and has 40% of the charging in hour 15.

profile adds about 1.3 MWh of renewable generation for each MWh of EV charging which leads to *negative* incremental 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.

Whether it is optimal to do this depends on the trade-offs between carbon emissions, other electricity consumption, and generation costs. We evaluate these trade-offs by considering the welfare gains from EV adoption for seven charging profiles (Table 6).[59] If the SCC is zero, then the Private Profile is optimal. This profile charges primarily at night (see Figure A.18), has welfare gains of $71 billion, and results in carbon emissions of from the electricity sector of 1,339 mmt (a 21% increase). If the SCC is $100 per ton, the Social Profile is optimal. This profile charges primarily during the day (see Figure A.18), has welfare gains of $134 billion, and results in carbon emissions of 1,243 mmt (a 12% increase). With lower renewable capital costs (Panel B of Table 6), the results are similar: the Private Profile increases carbon emissions by 18% and the Social Profile increases carbon emissions by 5%. 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.

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

[59]The calculation of welfare gains is described in detail in Online Appendix A.4. In addition to the consumer surplus, generation costs, capital costs, and externalities from the electricity sector, it accounts for the consumer surplus, operating costs, capital costs and externalities from driving gasoline vehicles. It does not account for the any cost to the consumers of charging vehicles at inconvenient times.

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 US 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 to apply to batteries that are co-located with solar investment (which also uses the Investment Tax Credit).

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 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.[60]

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. 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. In addition, actual solar and wind generation data for several missing regions would allow better

[60] See Section A.5 for a preliminary analysis of the effect of demand elasticity.

capacity factor estimates. Given these caveats, our theoretical and calibration results provide important insights for long-run electricity policy which short-run analysis cannot assess.

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Appendix: 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 $p_t \le c_{i'}$. But $q_{it} > 0$ implies that $p_t = c_i + \lambda_{it} \ge c_i$, which contradicts the assumption $c_i > c_{i'}$. ■

Lemma 2 *If $\sum_i f_{it}K_i > b_t$, then $p_t = \min_i\{\max\{c_i, U'(\sum_{i'\le i} f_{i't}K_{i'} - b_t)\}\}$.*
Proof: For notational simplicity, assume the technologies have unique costs. Because Lemma 1 implies a unique ordering of the technologies, let $\rho_{it} \equiv U'(\sum_{i'\le i} f_{i't}K_{i'} - b_t)$ be the marginal benefit if all technologies with marginal 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 $p_{t+1} \le p_t$. If $0 < S_t < \bar{S}$, then $p_{t+1} = p_t$. If $S_t = \bar{S}$, then $p_{t+1} \ge p_t$.*
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 $p_{t+1} - p_t = \phi_{t+1} - \phi_t \le 0$. 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 $\mu_t \ge 0$ and $0 = p_{t+1} - p_t - \mu_t \le p_{t+1} - p_t$, so $p_{t+1} \ge p_t$. ■

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 $p_t - c_i \le \lambda_{it}$. Because $\lambda_{it} \ge 0$ we have $\lambda_{it} \ge \max\{p_t - c_i, 0\}$. Proof by contradiction shows that $\lambda_{it} = \max\{p_t - c_i, 0\}$. Summing over all t establishes the first formula.[61] 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,

[61]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.

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 $\sum_{t\epsilon C}\mu_t$, 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 $\sum_{t\epsilon C}\mu_t = \bar{p} - \underline{p}$. To evaluate $\sum_{t\epsilon C} -p_t b_t$, 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, $\sum_{t\epsilon C} -p_t b_t = (\bar{p} - \underline{p})\bar{S}$. Dividing by $\bar{S}$ and summing over all charging cycles establishes the result.■

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 marginal cost and zero emissions, but technology 2 has positive marginal 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 2 *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.[62] ■

Result 3 *If the capital cost of renewables decreases then carbon emissions can increase or decrease, i.e.,* $\Delta \sum_i \sum_t \beta_i q_{it} \lesseqgtr 0$.

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 $p_B = r_2 - r_1$, 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 marginal cost and zero emissions, but technology 2 has positive marginal 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.

[62] 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.

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.■

Tables and Figures

Tables

Table 1: Capital and Marginal Costs for Different Technologies

	Overnight Cost ($/kW)	Annual Capital Cost ($/MW)	Marginal 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.

Table 2: Benefits of carbon pricing

Carbon Price ($/ton)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Welfare Gains ($ billions) for SCC of $0	$50	$100	$150	$200
0	37.65	1,107	**0.0**	0.0	0.0	0.0	0.0
50	50.92	554	-16.1	**11.6**	39.3	66.9	94.6
100	55.92	254	-38.6	4.1	**46.7**	89.4	132.0
150	56.52	78	-59.7	-8.2	43.2	**94.7**	146.1
200	56.04	26	-68.7	-14.6	39.5	93.6	**147.6**

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Electricity price is the quantity-weighted average price. Welfare gains are relative to the baseline without carbon pricing and include lost private surplus plus gains from carbon tax revenue and from reduced carbon emissions evaluated at the assumed SCC.

Table 3: Welfare gains of carbon tax and renewable subsidy interactions with battery

Carbon Tax	Renewable Subsidy					
	0	0.1	0.25	0.5	0.75	0.95
0	0.0	4.7	16.7	36.9	6.5	-193.8
10	6.8	12.5	31.8	38.0	2.7	-195.8
25	17.1	29.1	40.4	38.1	-2.3	-198.5
50	40.2	43.8	45.3	34.8	-8.5	-202.0
75	46.6	47.4	45.6	30.7	-13.1	-204.4
100	48.1	47.3	44.0	27.0	-16.2	-206.4
125	47.0	46.1	41.1	24.1	-18.3	-208.4

Notes: Welfare gains ($ billions annually) are relative to baseline with storage and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC of $100 minus any subsidy expenditures plus revenue from any carbon tax. A carbon tax of $100 and renewable subsidy of zero is first best.

Table 4: Second-best policies

	Annual Welfare Gains ($ billions) for SCC of			
Policy	$50	$100	$150	$200
Panel A: First best				
Pigouvian Carbon Tax	11.91	48.12	97.56	151.89
Panel B: Second-best subsidy				
Renewable	6.23	36.88	70.42	103.97
	[25]	[50]	[50]	[50]
Solar	3.47	17.55	33.34	54.43
	[25]	[50]	[50]	[75]
Wind	3.26	26.63	53.86	81.10
	[25]	[50]	[50]	[50]
Nuclear	0.00	13.34	60.75	108.17
	[40]	[50]	[50]	[50]
Battery	0.05	0.20	0.34	0.49
	[25]	[25]	[25]	[25]
Panel C: Relative gains of second-best subsidy combination				
Battery and Renewable	0.14	0.48	2.02	5.06
	[25,25]	[25,50]	[50,50]	[75,50]
Battery and Solar	0.08	0.44	2.43	7.19
	[25,25]	[25,50]	[50,50]	[50,75]
Battery and Wind	0.08	0.13	0.50	0.90
	[25,25]	[25,50]	[25,50]	[50,50]
Battery and Nuclear	0.00	0.37	1.46	3.18
	[25,0]	[25,50]	[50,50]	[50,50]
Renewable and Nuclear	0.00	0.12	5.25	6.19
	[25,0]	[50,50]	[50,50]	[50,50]
Solar and Wind	2.76	10.25	16.56	22.87
	[25,25]	[50,50]	[50,50]	[50,50]

Notes: Welfare gains are relative to baseline with storage 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. 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 second-best policy values in percentage cost reduction.

Table 5: Effects of electric vehicle adoption

Charging Profile	EV Share	Electricity Price ($/MWh)	CO_2 (mmt)	Incremental Emissions (mt/MWh)	Incremental Generation (MWh/MWh)	Incremental Renewables (MWh/MWh)
Panel A: Baseline renewable capital costs						
	0%	37.65	1,107	.	.	.
Convenience	50%	37.54	1,237	0.38	0.99	-0.13
	100%	37.07	1,361	0.37	0.98	-0.11
Carbon Minimizing	50%	35.29	1,139	0.09	0.96	0.71
	100%	31.58	1,183	0.11	0.98	0.72
Panel B: 25% reduction in renewable capital costs						
	0%	36.51	903	.	.	.
Convenience	50%	36.40	1,032	0.38	0.98	-0.13
	100%	35.98	1,148	0.36	0.98	-0.08
Carbon Minimizing	50%	34.68	857	-0.13	0.99	1.39
	100%	30.57	842	-0.09	1.02	1.32

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Incremental emissions is the change in emissions relative to the change in EV demand; incremental generation is the change in generation relative to the change in EV demand; and incremental renewables is the change in generation from wind plus solar relative to the change in EV demand.

Table 6: 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	37.07	1,361	68.2	96.2	124.2	152.2	180.2
Carbon Minimizing	31.58	1,183	45.4	82.3	119.2	156.1	193.0
Flat	37.65	1,340	68.5	97.6	126.7	155.7	184.8
Solar Profile	37.00	1,254	64.4	97.7	131.1	164.5	197.8
Wind Profile	37.64	1,344	68.4	97.3	126.2	155.1	183.9
Private Profile	37.30	1,339	71.1	100.2	129.3	158.4	187.5
Social Profile	36.81	1,243	66.5	100.4	134.4	168.3	202.2
Panel B: 25% reduction in renewable capital costs							
Convenience	35.98	1,148	60.4	88.9	117.3	145.8	174.2
Carbon Minimizing	30.57	842	36.0	79.8	123.5	167.3	211.0
Flat	36.52	1,103	60.2	90.9	121.6	152.3	183.0
Solar Profile	36.02	964	55.1	92.7	130.4	168.1	205.8
Wind Profile	36.51	1,111	60.2	90.6	120.9	151.2	181.6
Private Profile	36.09	1,066	62.5	95.0	127.6	160.2	192.7
Social Profile	35.71	946	55.9	94.4	133.0	171.6	210.1

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. 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.

Figures

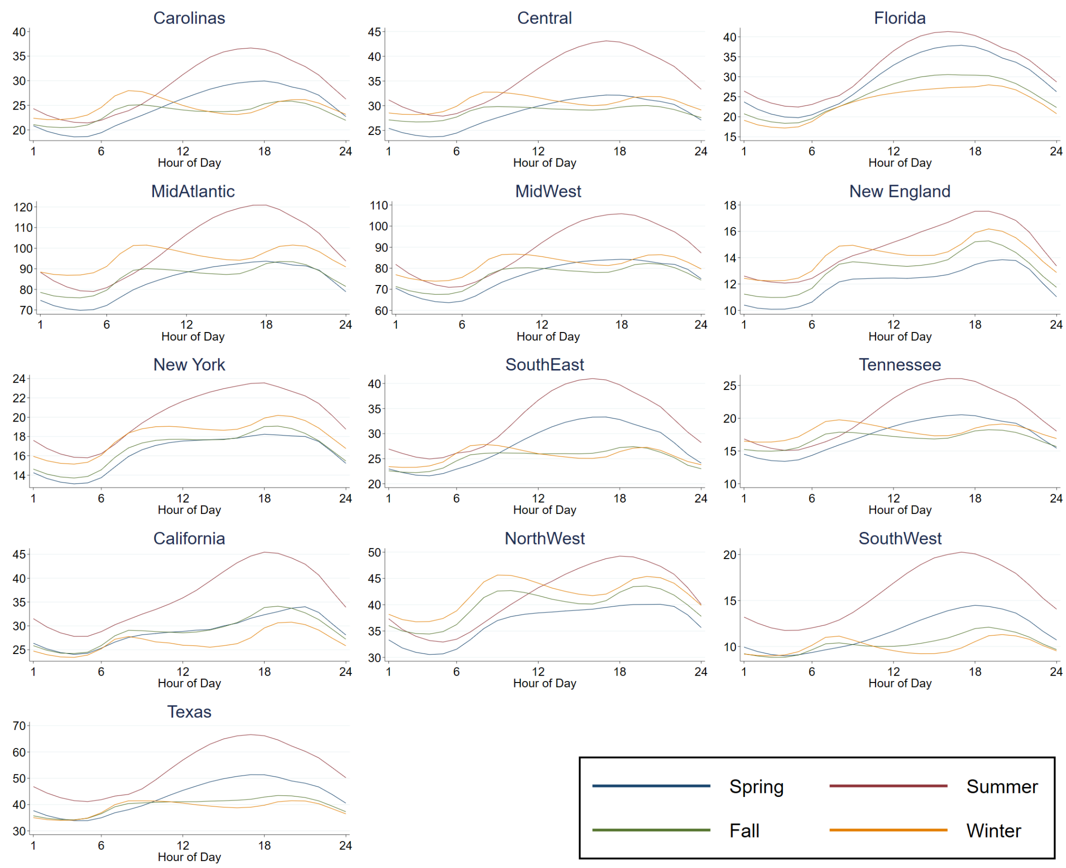


Figure 1: Mean hourly observed demand by season and hour of day for each EIA region.
Notes: Demand in thousands of MWh.

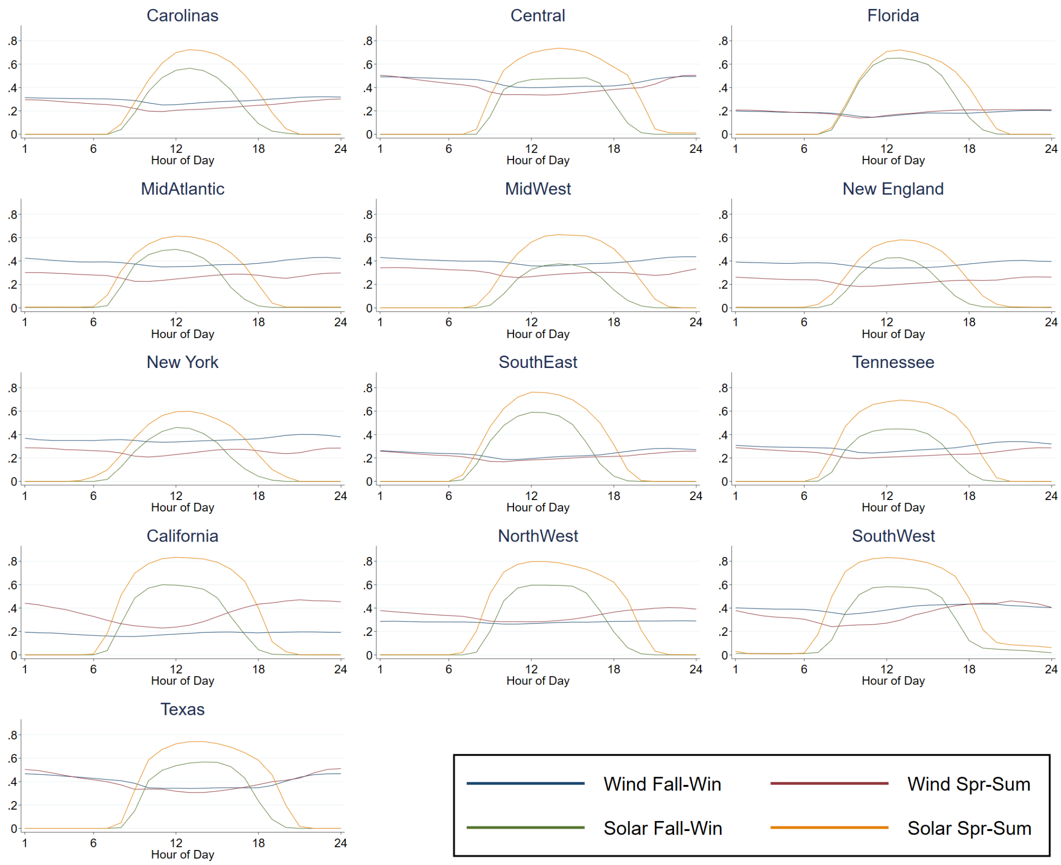
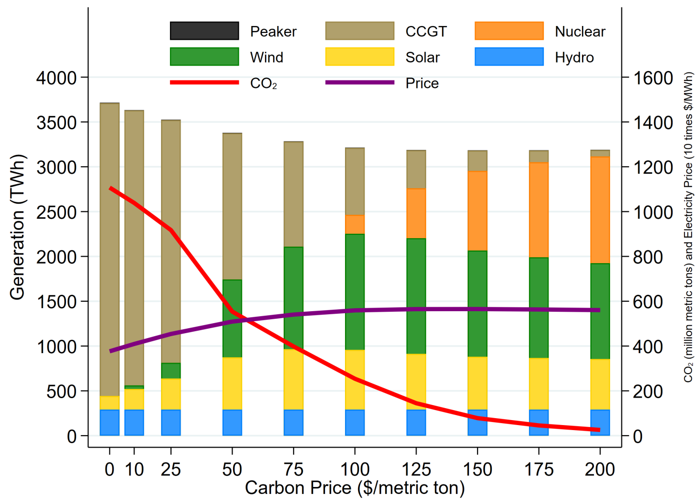
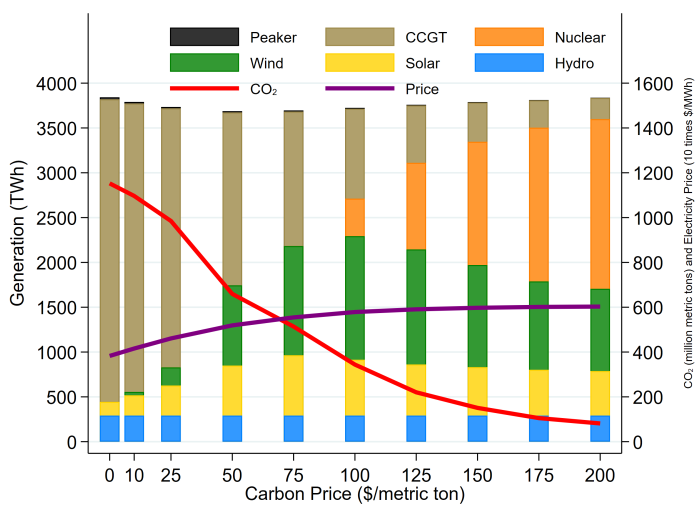


Figure 2: Mean hourly capacity factors by season and hour of day for each EIA region.



(a) Linear demand.



(b) Iso-elastic demand.

Figure 3: Carbon pricing aggregated across all regions.

Notes: Baseline parameterization with no storage and no interregional transmission. Results aggregated across all regions.

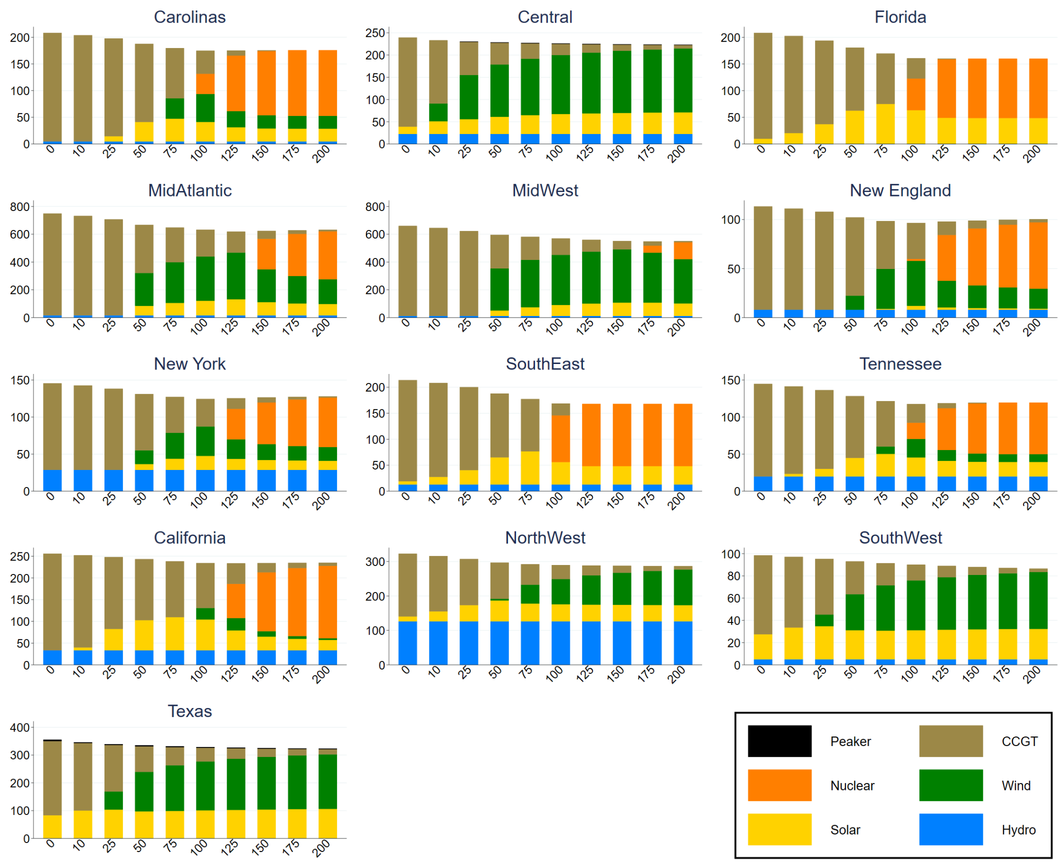


Figure 4: Carbon pricing for each region.

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission.

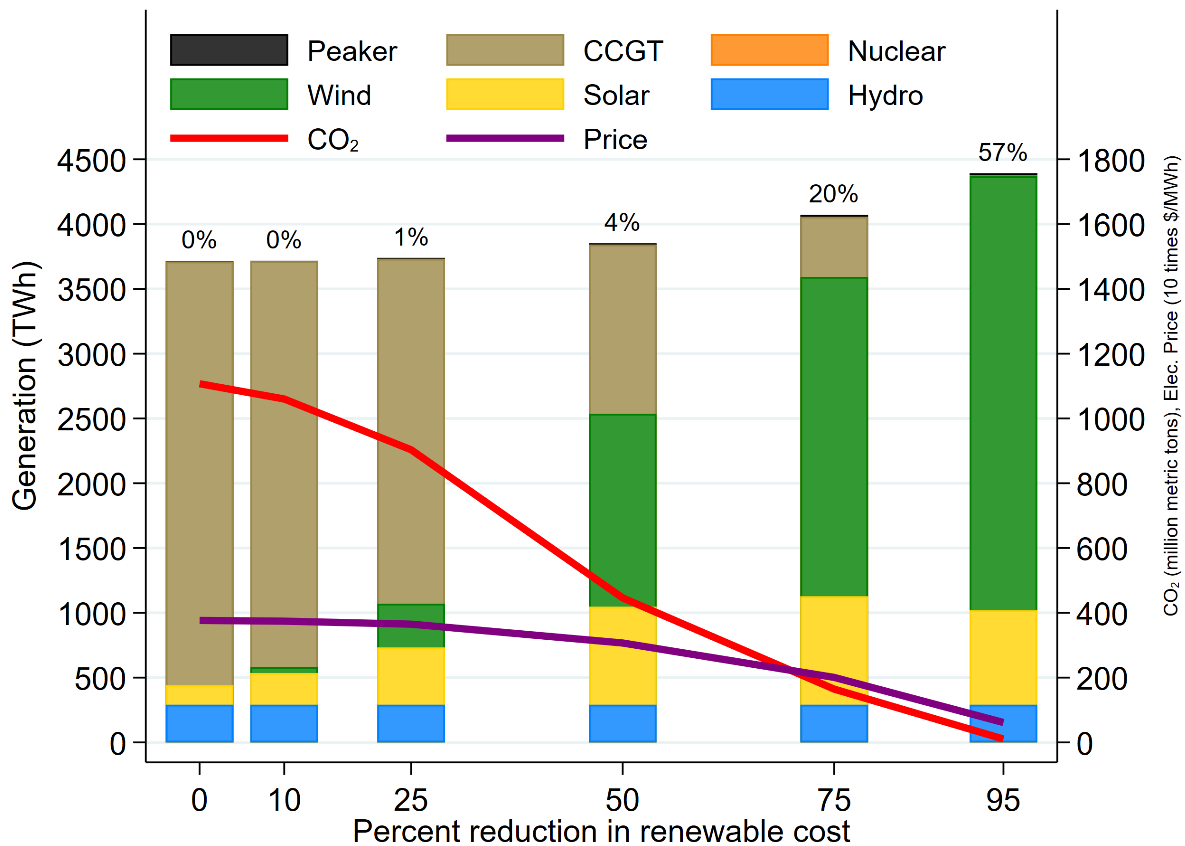


Figure 5: Reduction in renewable capital costs.

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Results aggregated across all regions. Generation is utilized generation, and the percentages show the percent of potential renewable generation which is curtailed (not utilized).

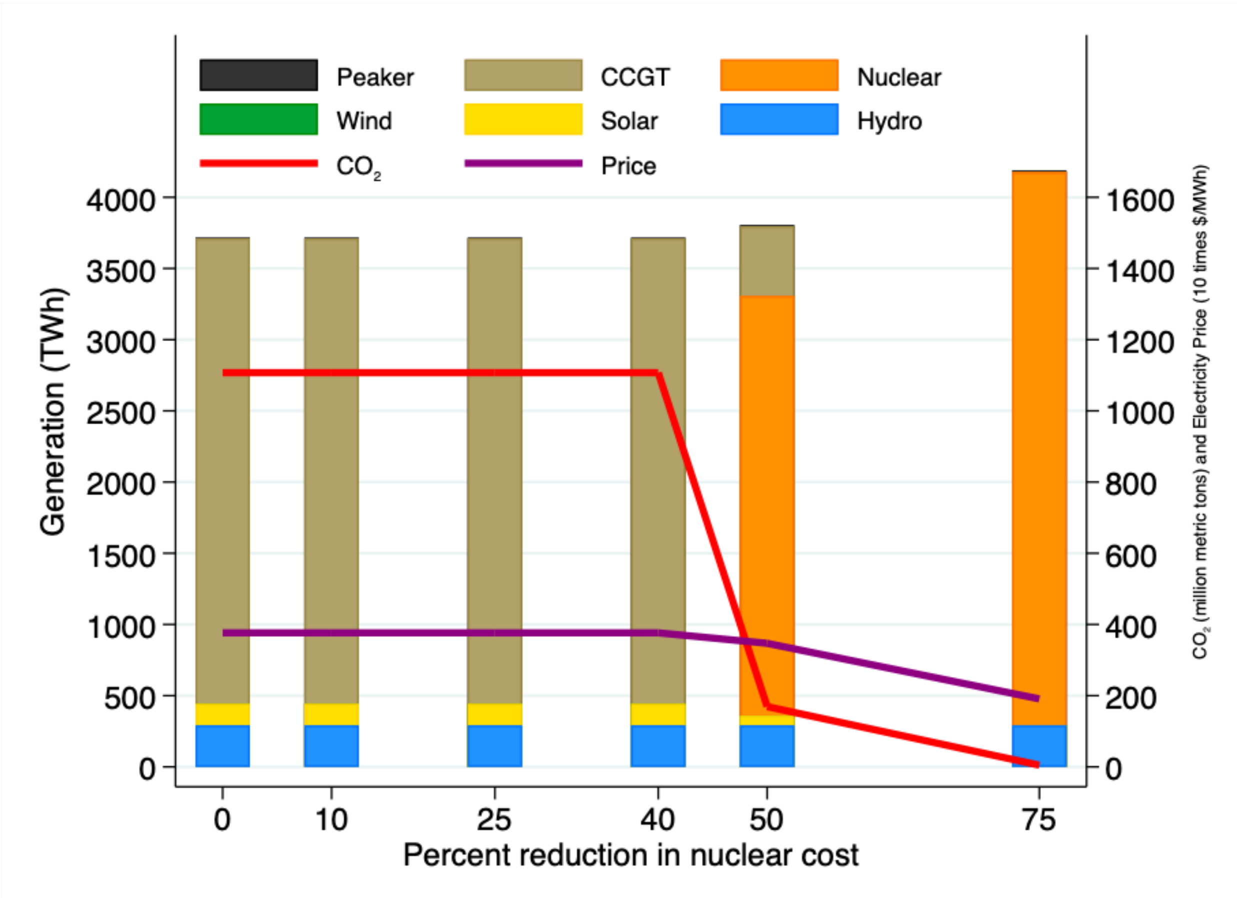
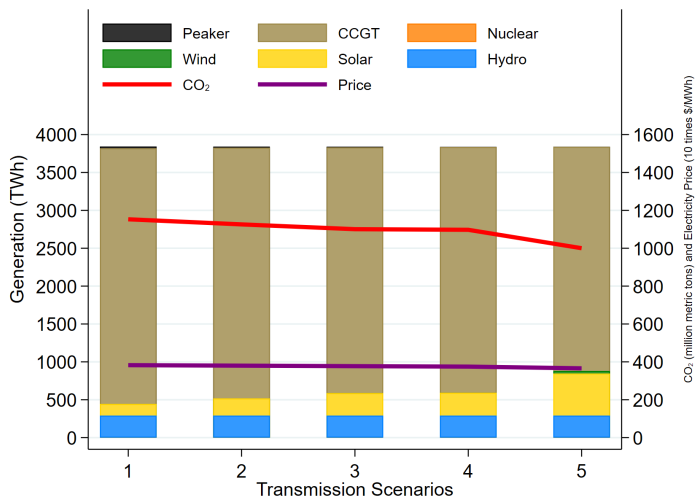
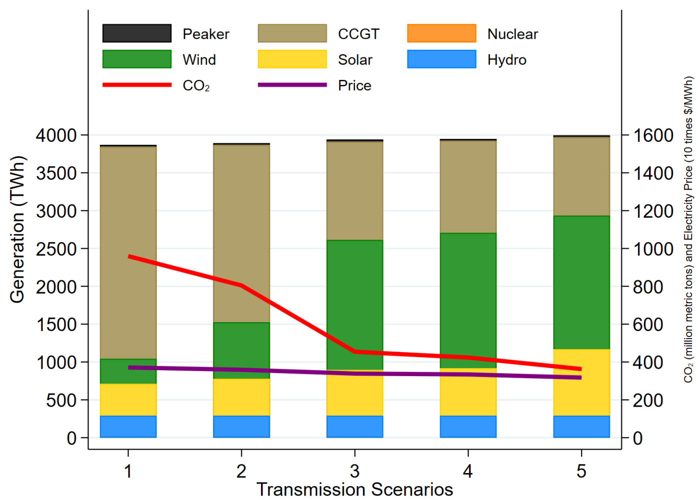


Figure 6: Reduction in nuclear capital costs.

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Results aggregated across all regions.



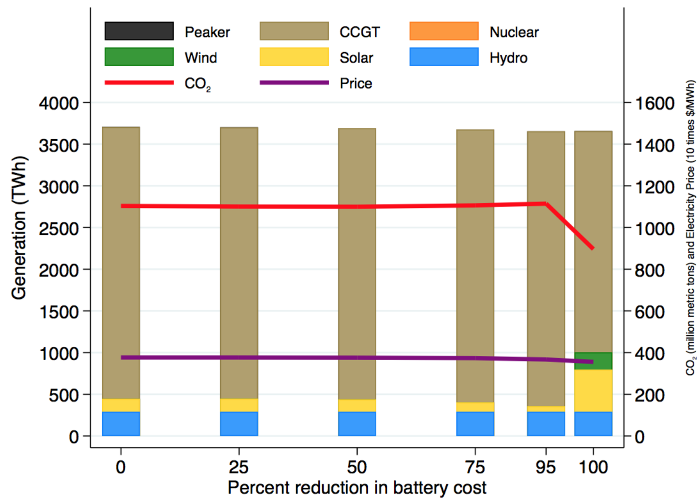
(a) Baseline renewable capital costs.



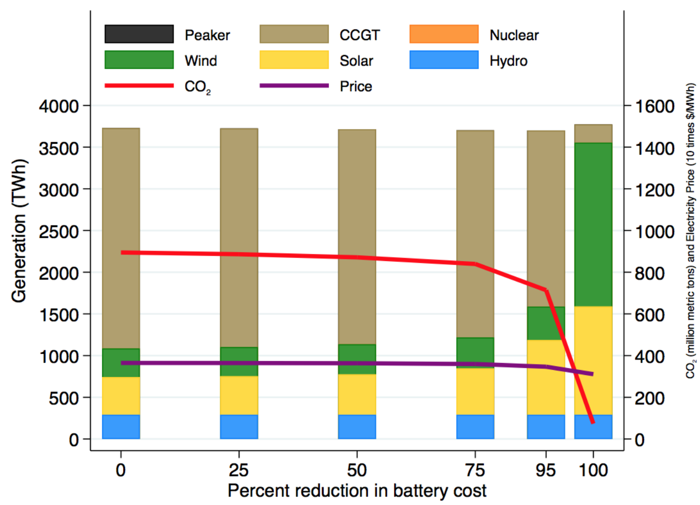
(b) 25% reduction in renewable capital costs.

Figure 7: Scenarios increasing transmission.

Notes: Baseline parameterization with iso-elastic demand and no storage. 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.



(a) Baseline renewable capital costs.



(b) 25% reduction in renewable capital costs.

Figure 8: Reduction in battery capital costs.

Baseline parameterization with linear demand and no interregional transmission aggregated across all regions.

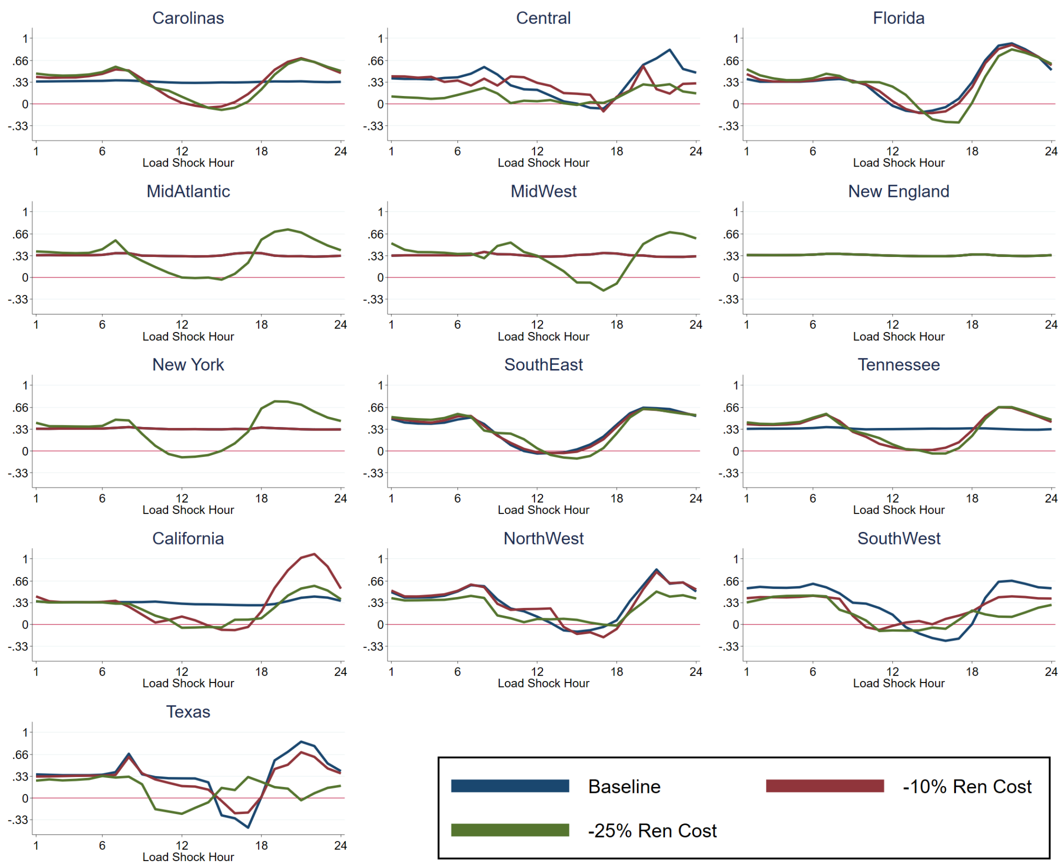


Figure 9: Incremental emissions by hour-of-day load shocks for each EIA region.
Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Scenarios show 10% and 25% reductions in renewable capital costs. Vertical axis is the change in emissions (lbs/kWh) across all hours from a one percent shock to load in only hour h each day of the year.

Online Appendices

A.1 Model with imperfect storage

The main model assumes that storage is perfect, *e.g.,* that there are no conversion losses from charging or discharging a battery and that the battery state does not decay over time. These assumptions may be more or less appropriate for different storage technologies, e.g., batteries, pumped hydropower storage, molten salt storage, flywheels, etc.

Here we extend the model in the main text to account for imperfect storage. Let $\beta \in [0,1]$ denote the conversion loss from charging or discharging the battery. Let $\alpha \in [0,1]$ denote the battery state decay rate. Let $b_{ct} \geq 0$ be the electricity drawn from the grid to charge the battery in period t and $b_{dt} \geq 0$ be the electricity injected into the grid from the battery discharge in period t. The state of the battery, S_t, depends on charges and discharges to the battery and evolves according to

$$S_t = \alpha S_{t-1} + (1-\beta) b_{ct} - (1+\beta) b_{dt}.$$

The electricity balance in each period requires that $Q_t + b_{ct} - b_{dt} \leq \sum_i q_{it}$, i.e., consumption plus net battery charge cannot exceed electricity generation from all sources.

With these modifications to the planner's problem, the new Kuhn-Tucker first-order conditions are

$$
\begin{aligned}
&Q_t \geq 0 && d\mathcal{L}/dQ_t = U_t'(Q_t) - p_t \leq 0 && \forall t && C.S. && (9)\\
&q_{it} \geq 0 && d\mathcal{L}/dq_{it} = -c_i + p_t - \lambda_{it} \leq 0 && \forall i,t && C.S. && (10)\\
&b_{ct} \geq 0 && -p_t + (1-\beta)\phi_t \leq 0 && \forall t && C.S. && (11)\\
&b_{dt} \geq 0 && p_t - (1+\beta)\phi_t \leq 0 && \forall t && C.S. && (12)\\
&S_t \geq 0 && d\mathcal{L}/dS_t = \alpha\phi_{t+1} - \phi_t - \mu_t \leq 0 && \forall t && C.S. && (13)\\
&K_i \geq 0 && d\mathcal{L}/dK_i = \sum_t \lambda_{it} f_{it} - r_i \leq 0 && \forall i && C.S. && (14)\\
&\bar{S} \geq 0 && d\mathcal{L}/d\bar{S} = \sum_t \mu_t - r_s \leq 0 && && C.S. && (15)
\end{aligned}
$$

A.2 Renewable capacity factors for missing regions

The EIA 930 is missing hourly solar generation for New York and hourly wind generation for Carolinas, Florida, SouthEast, and Tennessee. To estimate capacity factors for these missing regions we use the following procedures. 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).

To determine 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 different heights.[63] In particular, we use wind speed at 80 meters. For every county centroid in the US, we find the NREL site closest to the centroid, giving one observation per county per hour. Then we use an equation from the engineering literature to convert wind speed into an estimated capacity factor by county by hour (ECFH).[64] 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

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

[64] 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`.

do not have actual 2019 capacity factor data. Finally these predictions are bounded by zero and one.

A.3 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.[65]

Using these coarsened time periods, we first analyze the effects of carbon pricing. Figure A.4 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 3 but is similar to Stock and Stuart (2021) who use a modified version of the NREL

[65]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.

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 A.5 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.

A.4 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 give by gross consumer surplus (CS_e) minus costs of electricity $Cost_e$ (the sum of marginal 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 capital costs (V_{GV}). In the initial equilibrium total welfare is given by

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

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 given by

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

where CS_{EV} is the gross consumer surplus from driving EV's and V_{EV} is the capital cost of EV's. 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 in Table A.17. We have

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

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

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

A.5 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 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

$$\max_{q_{it}, b_t, S_t, K_i, \bar{S}} \sum_t [-\sum_i c_i q_{it}] - \sum_i r_i K_i - r_s \bar{S}, \tag{16}$$

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 A.18.

Comparing the results to Table A.10 we see that fixing demand does generally give greater benefits to batteries.

Online Appendix Tables and Figures

Online Appendix Tables

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

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

	2014	2015	2016	2017	2018	2019	2020	2021
Combined cycle								
Annual Capital	162359	161683	152297	150393	135193	76978	86315	79489
Marginal Cost	51.29	59.54	42.48	41.08	34.00	32.47	27.21	26.68
Combustion turbine								
Annual Capital	98938	99246	90970	90684	81582	63652	59288	54741
Marginal Cost	79.24	88.41	68.79	67.61	58.81	55.86	44.87	44.13
Wind (onshore)								
Annual Capital	277511	257806	246797	234672	223749	207297	141682	132602
Solar PV								
Annual Capital	320907	304792	202555	192929	169527	157360	91869	83274
Battery Storage								
Annual Capital	NA	NA	NA	NA	NA	NA	NA	84087
Advanced nuclear								
Annual Capital	749146	726830	787741	742188	693446	551739	579158	528307
Marginal Cost	13.30	13.55	12.34	12.62	9.82	9.79	9.17	2.38

Notes: Source EIA (2021) .

Table A.3: Projections of Annual Overnight Capital Costs by Technology

Technology	2021	2026	2035	2050
Combined cycle	65125	63482	55154	44637
Combustion turbine	48273	45899	39152	31184
Wind (onshore)	86273	86128	76116	62491
Solar PV	83839	71338	58266	43603
Battery Storage	79294	58628	43830	37846
Advanced nuclear	431123	413851	354285	273892

Notes: Source EIA (2021) . These annual capital costs do not include fixed operating and maintenance and transmission costs.

Table A.4: Benefits of carbon pricing (Iso-elastic demand)

Carbon Price ($/ton)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Welfare Gains ($ billions) for SCC of $0	$50	$100	$150	$200
0	38.26	1,153	0.0	0.0	0.0	0.0	0.0
50	51.90	659	-14.4	10.3	34.9	59.6	84.3
100	57.85	344	-38.5	2.0	42.4	82.9	123.3
150	59.75	151	-61.7	-11.6	38.5	88.6	138.7
200	60.29	81	-73.4	-19.8	33.8	87.3	140.9

Notes: Baseline parameterization with iso-elastic demand, no storage, and no interregional transmission. Electricity price is the quantity-weighted average price. Welfare gains are relative to the baseline without carbon pricing and include lost private surplus plus gains from carbon tax revenue and from reduced carbon emissions evaluated at the assumed SCC.

Table A.5: 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
0	37.65	1,107	0.0	0.0	0.0	0.0	0.0	0.0
25	36.51	903	3.6	13.8	24.0	34.2	44.4	7.7
50	30.69	446	21.4	54.5	87.6	120.6	153.7	51.5
75	20.07	165	57.3	104.5	151.6	198.7	245.9	146.4
95	6.14	10	113.8	168.6	223.5	278.3	333.2	424.4

Notes: Baseline parameterization with linear demand, no storage, no interregional transmission, and no carbon tax. 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 A.6: Benefits of reducing renewable capital costs (Iso-elastic demand)

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill
0	38.26	1,153	0.0	0.0	0.0	0.0	0.0	0.0
25	37.12	960	3.6	13.2	22.9	32.5	42.2	7.4
50	31.05	488	21.2	54.4	87.7	121.0	154.2	52.3
75	18.33	212	58.2	105.3	152.3	199.4	246.4	149.3
95	4.11	48	116.1	171.3	226.6	281.8	337.1	435.6

Notes: Baseline parameterization with iso-elastic demand, no storage, no interregional transmission, and no carbon tax. 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 A.7: 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	1,107	0.0	0.0	0.0	0.0	0.0	0.0
25	37.65	1,107	0.0	0.0	0.0	0.0	0.0	0.0
40	37.65	1,107	0.0	0.0	0.0	0.0	0.0	0.0
50	34.71	169	8.4	55.3	102.2	149.1	196.0	89.2
75	19.10	5	63.4	118.6	173.7	228.8	283.9	190.3

Notes: Baseline parameterization with linear demand, no storage, no interregional transmission, and no carbon tax. 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 A.8: 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	38.26	1,153	0.0	0.0	0.0	0.0	0.0	N.A.
Scenario 2	38.00	1,126	1.4	2.7	4.1	5.4	6.8	N.A.
Scenario 3	37.74	1,101	2.6	5.2	7.8	10.4	13.0	N.A.
Scenario 4	37.50	1,097	3.7	6.5	9.2	12.0	14.8	N.A.
Scenario 5	36.59	1,000	7.4	15.0	22.7	30.3	37.9	N.A.
Panel B: 25% reduction in renewable capital costs								
Scenario 1	37.12	960	3.6	13.2	22.9	32.5	42.2	7.4
Scenario 2	35.90	804	7.9	25.3	42.7	60.1	77.5	11.5
Scenario 3	33.88	454	15.0	49.9	84.9	119.8	154.8	21.1
Scenario 4	33.43	424	16.8	53.2	89.7	126.1	162.6	22.0
Scenario 5	31.76	363	22.3	61.8	101.4	140.9	180.4	22.8

Notes: Baseline parameterization with iso-elastic demand, no carbon tax, and no storage. Electricity price is the quantity-weighted average price. In panel A the benefits are relative to the baseline and are gains in private surplus plus gains from reduced carbon emissions evaluated at the assumed SCC. In panel B the benefits are relative to 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. 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 A.9: 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 2 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 A.10: 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	1,107	0.0	0.0	0.0	0.0	0.0	N.A.	N.A.
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	N.A.
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	N.A.
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	N.A.
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	N.A.
100	35.55	897	11.5	22.0	32.6	43.1	53.6	4,343	N.A.
Panel B: 25% reduction in renewable capital costs									
No Storage	36.51	903	3.6	13.8	24.0	34.2	44.4	N.A.	7.7
0	36.49	895	3.8	14.4	25.0	35.7	46.3	0.0	7.9
25	36.44	886	4.1	15.1	26.2	37.2	48.3	0.4	8.0
50	36.33	871	4.8	16.6	28.3	40.1	51.9	2.0	8.4
75	35.97	840	6.4	19.8	33.2	46.6	59.9	8.2	9.1
100	31.08	74	26.1	77.8	129.5	181.2	232.9	7,823	.
Panel C: 50% reduction in renewable capital costs									
No Storage	30.69	446	21.4	54.5	87.6	120.6	153.7	N.A.	51.5
0	30.62	433	21.9	55.6	89.3	123.1	156.8	0.0	52.0
25	30.52	420	22.4	56.7	91.1	125.4	159.8	0.7	52.5
50	30.26	395	23.5	59.1	94.8	130.4	166.0	3.5	53.7
75	29.29	292	27.1	67.9	108.6	149.4	190.2	20.3	60.0
100	20.80	0	63.6	119.0	174.3	229.7	285.1	8,767	.
Panel D: 75% reduction in renewable capital costs									
No Storage	20.07	165	57.3	104.5	151.6	198.7	245.9	N.A.	146.4
0	19.92	147	58.0	106.0	154.0	202.1	250.1	0.0	147.1
25	19.72	134	58.8	107.4	156.1	204.7	253.4	1.1	147.7
50	19.29	110	60.5	110.4	160.3	210.1	260.0	5.4	148.5
75	17.90	52	66.1	118.9	171.7	224.5	277.3	31.0	146.8
100	10.41	0	104.2	159.6	214.9	270.3	325.7	9,349	.

Notes: Baseline parameterization with linear demand, no interregional transmission, and no carbon tax. 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 battery capacity (Battery) or renewable capacity (Renew) without innovation.

Table A.11: Benefits of reducing battery capital costs and carbon tax

Cost Reduction (%)	Electricity Price ($/MWh)	CO_2 (mmt)	Annual Benefits ($ billions) for SCC of $0	$50	$100	$150	$200	Subsidy Cost $ bill
Panel A: Carbon Tax 0								
Baseline	37.65	1,107	0.0	0.0	0.0	0.0	0.0	N.A.
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8
Panel B: Carbon Tax 50								
No Storage	50.92	554	-16.1	11.6	39.3	66.9	94.6	N.A.
0	50.81	537	-16.3	12.2	40.7	69.3	97.8	0.0
25	50.70	525	-16.3	12.8	41.9	71.1	100.2	0.8
50	50.42	502	-16.3	14.0	44.3	74.6	104.8	3.4
75	49.53	436	-16.8	16.8	50.4	84.0	117.6	14.2
Panel C: Carbon Tax 100								
No Storage	55.92	254	-38.6	4.1	46.7	89.4	132.0	N.A.
0	55.48	221	-40.0	4.3	48.6	92.9	137.3	0.0
25	55.09	201	-40.6	4.7	50.0	95.3	140.6	1.9
50	54.09	169	-40.9	6.0	52.9	99.8	146.7	9.2
75	51.47	116	-39.0	10.5	60.1	109.6	159.2	31.1
Panel D: Carbon Tax 150								
No Storage	56.52	78	-59.7	-8.2	43.2	94.7	146.1	N.A.
0	55.57	46	-61.0	-7.9	45.2	98.2	151.3	0.0
25	54.96	37	-60.3	-6.8	46.7	100.2	153.8	2.6
50	53.64	31	-57.4	-3.6	50.2	104.0	157.8	11.5
75	50.68	20	-50.5	3.9	58.2	112.6	166.9	36.9
Panel E: Carbon Tax 200								
No Storage	56.04	26	-68.7	-14.6	39.5	93.6	147.6	N.A.
0	54.82	2	-68.3	-13.0	42.2	97.5	152.7	0.0
25	54.31	1	-66.2	-10.9	44.4	99.7	155.0	2.8
50	53.14	2	-62.1	-6.9	48.4	103.6	158.9	11.3
75	50.32	5	-53.0	2.1	57.3	112.4	167.5	37.8

Notes: Baseline parameterization with linear demand and no interregional transmission. Electricity price is the quantity-weighted average price. Benefits are relative to the baseline and include lost private surplus plus gains from carbon tax revenue and from reduced carbon emissions evaluated at the assumed SCC. "Subsidy Cost' is the subsidy that would be required to induce an equivalent battery capacity without innovation.

Table A.12: 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	1,107	0.0	0.0	0.0	0.0	0.0	N.A.	N.A.
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	N.A.
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	N.A.
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	N.A.
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	N.A.
Panel B: 25% reduction in solar capital costs									
No Storage	36.84	1,000	2.7	8.1	13.5	18.9	24.2	N.A.	4.7
0	36.84	993	2.9	8.6	14.3	20.0	25.7	0.0	4.8
25	36.82	988	3.1	9.1	15.1	21.1	27.0	0.4	4.9
50	36.74	976	3.7	10.3	16.8	23.4	29.9	1.7	5.1
75	36.43	946	5.2	13.3	21.4	29.4	37.5	7.9	5.8
Panel C: 50% reduction in solar capital costs									
No Storage	34.20	800	10.9	26.3	41.6	57.0	72.3	N.A.	24.7
0	34.19	788	11.2	27.2	43.2	59.2	75.2	0.0	25.2
25	34.12	775	11.7	28.3	44.9	61.6	78.2	0.6	25.8
50	33.91	741	12.8	31.1	49.4	67.7	86.0	3.5	27.7
75	32.66	571	16.9	43.7	70.5	97.4	124.2	25.5	38.9
Panel D: 75% reduction in solar capital costs									
No Storage	29.39	698	26.5	46.9	67.4	87.8	108.3	N.A.	56.8
0	29.31	676	27.1	48.7	70.3	91.8	113.4	0.0	58.1
25	29.12	649	28.1	51.0	73.9	96.8	119.7	1.5	60.4
50	28.19	504	31.4	61.6	91.8	122.0	152.1	14.0	75.7
75	23.84	185	45.4	91.5	137.7	183.8	229.9	65.9	117.9

Notes: Baseline parameterization with linear demand and no interregional transmission. 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 A.13: 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	1,107	0.0	0.0	0.0	0.0	0.0	N.A.	N.A.
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	N.A.
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	N.A.
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	N.A.
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	N.A.
Panel B: 25% reduction in wind capital costs									
No Storage	37.24	992	1.1	6.8	12.6	18.3	24.1	N.A.	3.7
0	37.23	987	1.3	7.3	13.3	19.3	25.3	0.0	3.7
25	37.18	983	1.5	7.8	14.0	20.2	26.5	0.4	3.7
50	37.07	975	2.1	8.7	15.3	21.9	28.5	1.7	3.9
75	36.78	970	3.7	10.5	17.4	24.3	31.1	8.0	4.4
Panel C: 50% reduction in wind capital costs									
No Storage	32.95	566	13.7	40.7	67.8	94.8	121.9	N.A.	41.4
0	32.91	559	13.9	41.3	68.8	96.2	123.6	0.0	41.6
25	32.83	552	14.3	42.0	69.8	97.6	125.4	0.5	42.1
50	32.61	538	15.2	43.6	72.1	100.5	129.0	2.8	43.3
75	32.05	508	17.6	47.5	77.4	107.4	137.3	11.3	45.5
Panel D: 75% reduction in wind capital costs									
No Storage	23.34	267	45.1	87.2	129.2	171.2	213.2	N.A.	135.9
0	23.24	256	45.5	88.1	130.7	173.3	215.8	0.0	136.4
25	23.07	243	46.2	89.4	132.7	175.9	219.1	1.0	137.3
50	22.67	218	47.7	92.2	136.6	181.1	225.5	4.6	139.5
75	21.70	172	51.6	98.3	145.1	191.8	238.6	18.4	145.0

Notes: Baseline parameterization with linear demand and no interregional transmission. 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 A.14: 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	1,107	0.0	0.0	0.0	0.0	0.0	N.A.	N.A.
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	N.A.
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	N.A.
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	N.A.
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	N.A.
Panel B: 25% reduction in nuclear capital costs									
No Storage	37.65	1,107	-0.0	-0.0	-0.0	-0.0	-0.0	N.A.	0.0
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	0.0
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	0.0
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	0.0
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	0.0
Panel C: 40% reduction in nuclear capital costs									
No Storage	37.65	1,107	0.0	0.0	0.0	0.0	0.0	N.A.	0.0
0	37.65	1,104	0.1	0.3	0.5	0.7	0.9	0.0	0.0
25	37.63	1,101	0.3	0.7	1.0	1.3	1.6	0.3	0.0
50	37.56	1,100	0.8	1.2	1.5	1.9	2.3	1.5	0.0
75	37.35	1,106	2.1	2.2	2.2	2.3	2.3	6.8	0.0
Panel D: 50% reduction in nuclear capital costs									
No Storage	34.71	169	8.4	55.3	102.2	149.1	196.0	N.A.	89.2
0	34.70	155	8.6	56.2	103.8	151.4	199.0	0.0	90.0
25	34.65	143	8.9	57.1	105.3	153.5	201.8	0.5	90.7
50	34.51	121	9.7	59.0	108.3	157.6	207.0	2.3	92.5
75	34.18	97	11.5	62.0	112.6	163.1	213.6	8.2	95.4
Panel E: 75% reduction in nuclear capital costs									
No Storage	19.10	5	63.4	118.6	173.7	228.8	283.9	N.A.	190.3
0	19.10	4	63.6	118.8	174.0	229.1	284.3	0.0	188.8
25	19.06	1	63.9	119.3	174.6	229.9	285.2	0.5	187.6
50	18.98	0	64.8	120.1	175.5	230.9	286.2	2.3	184.9
75	18.78	0	66.5	121.9	177.3	232.6	288.0	7.6	181.8

Notes: Baseline parameterization with linear demand and no interregional transmission. 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 A.15: 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: 25% reduction in nuclear capital costs									
0	37.65	1,104	0.0	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	0.0
50	30.62	433	21.7	55.3	88.8	122.4	155.9	52.0	0.0
75	19.92	147	57.9	105.7	153.6	201.4	249.2	147.1	0.0
Panel C: 40% reduction in nuclear capital costs									
0	37.65	1,104	-0.0	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	0.0
50	30.62	433	21.7	55.3	88.8	122.4	155.9	52.0	0.0
75	19.92	147	57.9	105.7	153.6	201.4	249.2	147.1	0.0
Panel D: 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
Panel E: 75% reduction in nuclear capital costs									
0	19.10	4	63.5	118.5	173.5	228.5	283.5	0.0	188.8
25	19.10	2	63.6	118.6	173.7	228.7	283.8	0.3	187.0
50	18.96	0	64.5	119.7	174.9	230.0	285.2	3.6	180.3
75	17.33	0	70.4	125.6	180.7	235.9	291.1	49.4	131.1

Notes: Baseline parameterization with linear demand and no interregional transmission. 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 renewable capacity (Renew) or nuclear capacity (Nuclear) without innovation.

Table A.16: Benefits of reducing solar 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 Solar	Wind
Panel A: Baseline wind capital costs									
0	37.65	1,104	0.0	0.0	0.0	0.0	0.0	0.0	N.A.
25	36.84	993	2.8	8.3	13.8	19.3	24.8	4.8	N.A.
50	34.19	788	11.1	26.9	42.7	58.5	74.3	25.2	N.A.
75	29.31	676	27.0	48.4	69.8	91.1	112.5	58.1	N.A.
Panel B: 25% reduction in wind capital costs									
0	37.23	987	1.1	7.0	12.8	18.6	24.5	0.0	3.7
25	36.49	895	3.7	14.1	24.6	35.0	45.4	4.6	3.3
50	33.94	712	11.7	31.3	50.9	70.5	90.0	24.0	2.9
75	29.25	651	27.1	49.8	72.4	95.1	117.7	57.2	1.0
Panel C: 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	32.42	505	15.6	45.6	75.5	105.5	135.4	3.4	39.6
50	30.62	433	21.7	55.3	88.8	122.4	155.9	17.7	34.2
75	27.06	383	33.9	69.9	105.9	141.9	177.9	47.2	28.4
Panel D: 75% reduction in wind capital costs									
0	23.24	256	45.4	87.8	130.2	172.6	215.0	0.0	136.4
25	23.14	237	46.0	89.4	132.7	176.1	219.4	1.5	132.4
50	22.31	193	49.3	94.8	140.4	185.9	231.5	11.4	122.7
75	19.92	147	57.9	105.7	153.6	201.4	249.2	35.8	111.3

Notes: Baseline parameterization with linear demand and no interregional transmission. 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 solar capacity (Solar) or wind capacity (Wind) without innovation.

Table A.17: Parameters for EV welfare calculations

Name	Value	Source	Notes
CO_2 emissions	313 g/mile	Holland et al. (2021)	2015 model year vehicles
VMT	2600.406 billion miles	Holland et al. (2021)	Light duty vehicles
Capital premium	10689.57	Holland et al. (2021)	Premium for 2017 model year
Vehicle sales	17 million cars /year		
Gasoline price	$3/gallon		

Table A.18: 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	37.82	1,234	0.0	0.0	0.0	0.0	0.0	N.A.	N.A.
0	37.72	1,232	0.4	0.5	0.6	0.7	0.8	0.0	N.A.
25	37.68	1,224	0.6	1.0	1.5	2.0	2.4	0.2	N.A.
50	37.57	1,217	1.0	1.8	2.7	3.5	4.3	1.6	N.A.
75	37.06	1,212	3.1	4.1	5.2	6.3	7.3	12.8	N.A.
100	32.99	990	19.4	31.6	43.8	56.0	68.1	4,569	N.A.
Panel B: 25% reduction in renewable capital costs									
No Storage	36.92	1,045	3.6	13.0	22.5	31.9	41.3	N.A.	6.7
0	36.78	1,027	4.2	14.5	24.9	35.2	45.6	0.0	7.2
25	36.68	1,016	4.6	15.5	26.4	37.2	48.1	0.5	7.5
50	36.45	984	5.5	18.0	30.4	42.9	55.4	2.7	8.5
75	35.88	946	7.8	22.2	36.5	50.9	65.3	11.7	9.6
100	29.03	80	35.4	93.0	150.7	208.4	266.1	8,183	36.1
Panel C: 50% reduction in renewable capital costs									
No Storage	33.51	606	17.3	48.7	80.1	111.4	142.8	N.A.	45.7
0	33.15	584	18.8	51.3	83.7	116.2	148.7	0.0	46.9
25	32.94	565	19.6	53.1	86.5	120.0	153.4	1.2	48.3
50	32.44	531	21.7	56.8	92.0	127.1	162.3	5.9	50.3
75	31.22	448	26.6	65.8	105.1	144.4	183.7	23.9	55.0
100	19.40	0	74.1	135.7	197.4	259.1	320.8	8,640	78.0
Panel D: 75% reduction in renewable capital costs									
No Storage	25.64	306	49.0	95.4	141.7	188.1	234.5	N.A.	128.6
0	25.14	289	51.0	98.2	145.4	192.7	239.9	0.0	128.5
25	24.83	270	52.3	100.4	148.6	196.8	244.9	1.9	129.8
50	24.14	245	55.0	104.4	153.8	203.3	252.7	7.2	131.5
75	22.36	168	62.2	115.5	168.7	222.0	275.3	36.2	133.7
100	9.70	0	113.1	174.8	236.5	298.1	359.8	8,640	117.1

Notes: Baseline parameterization with no interregional transmission, and no carbon tax. Electricity price is the total cost divided by total production. 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

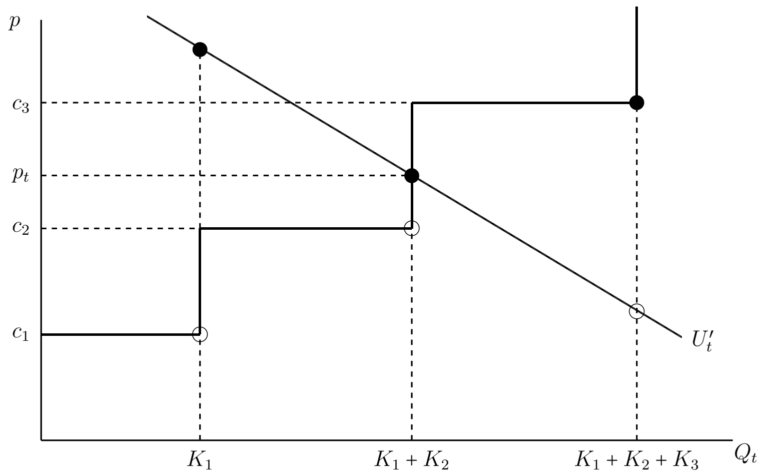


Figure A.1: Illustrative supply and demand with market clearing price p_t.
Notes: To illustrate Lemma 2, this figure assumes no storage and three technologies with capacity factors equal to one. The electricity price is determined by the intersection of the smooth demand curve U_t' and the step function 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. $p_t = U_t'(K_1 + K_2)$.

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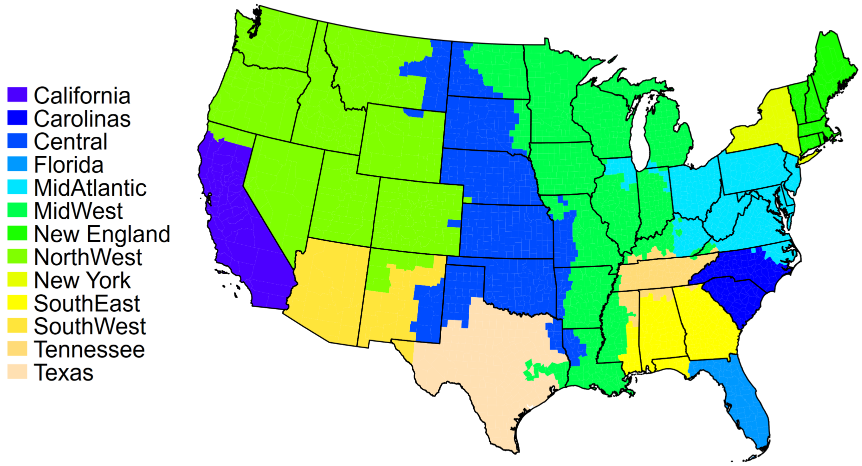


Figure A.2: Map of EIA regions.

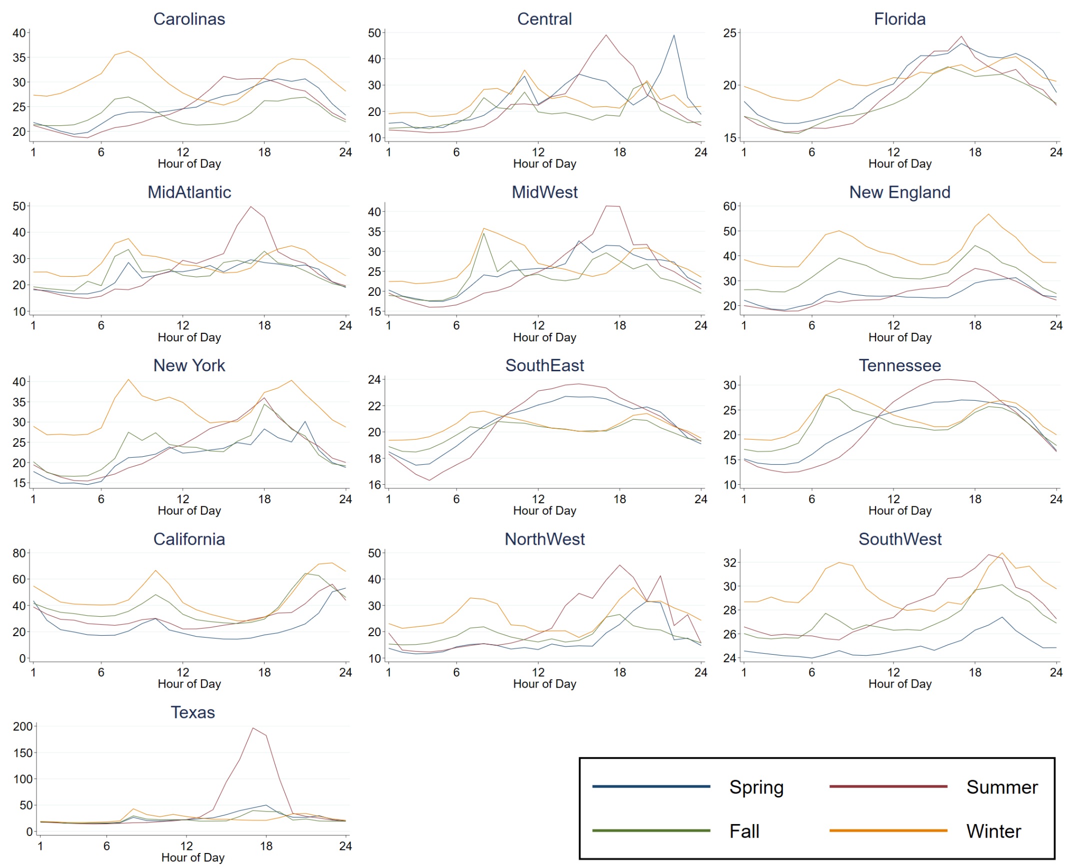


Figure A.3: Mean hourly observed price by season for each EIA region.

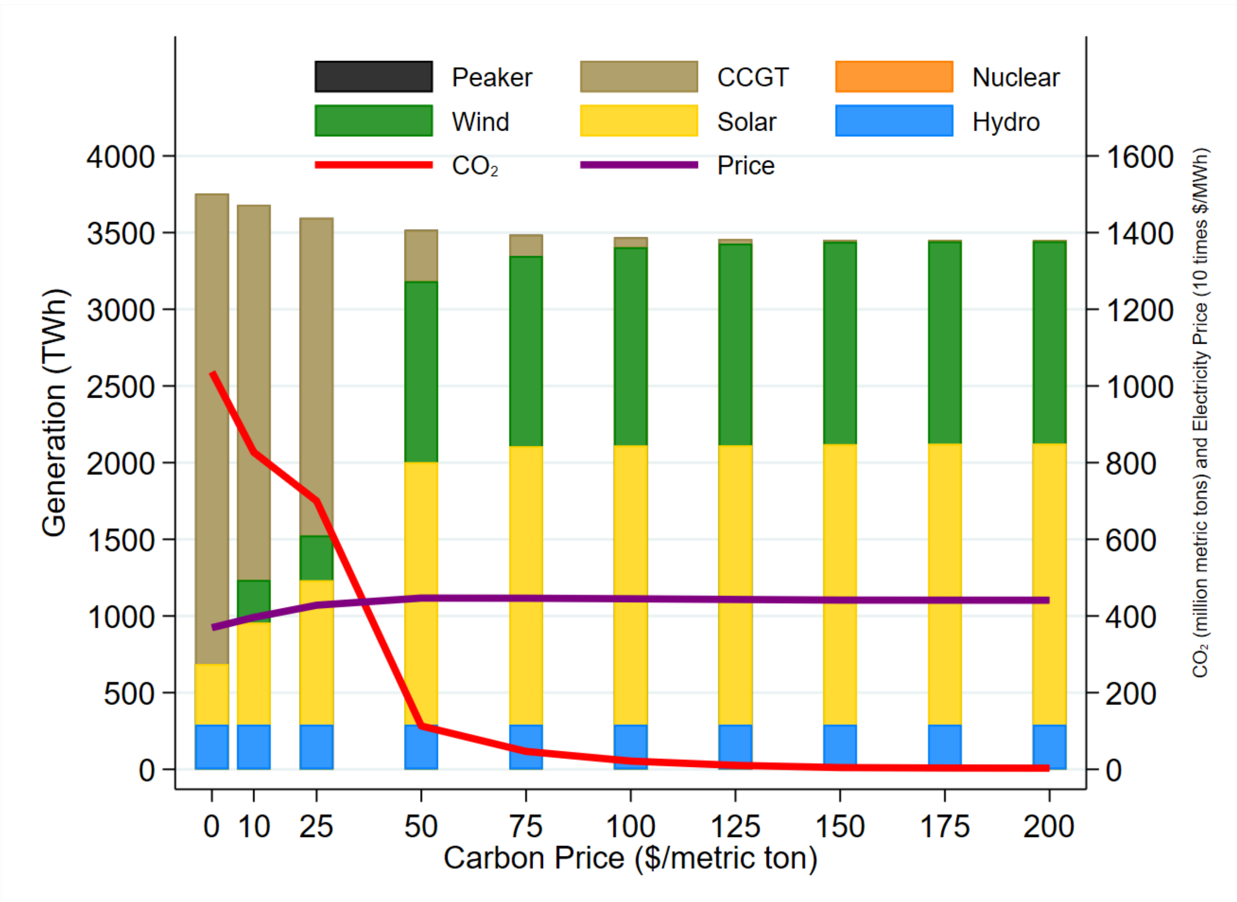


Figure A.4: Carbon pricing with NEMS time periods.

Notes: Baseline parameterization with linear demand for nine NEMS time periods, no storage, and no interregional transmission aggregated across all regions.

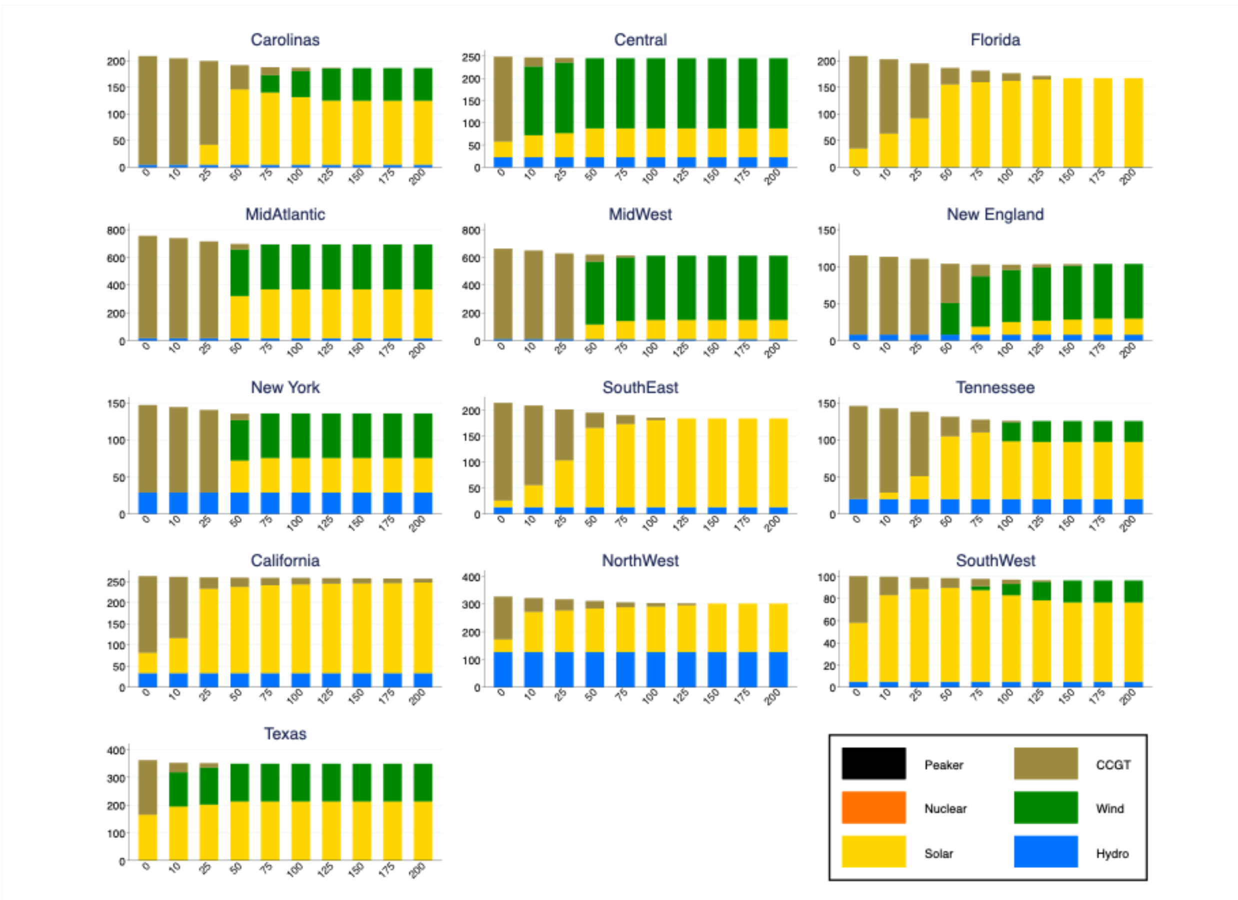


Figure A.5: Carbon pricing with NEMS time periods for each region

Notes: Baseline parameterization with linear demand for nine NEMS time periods, no storage, and no interregional transmission.

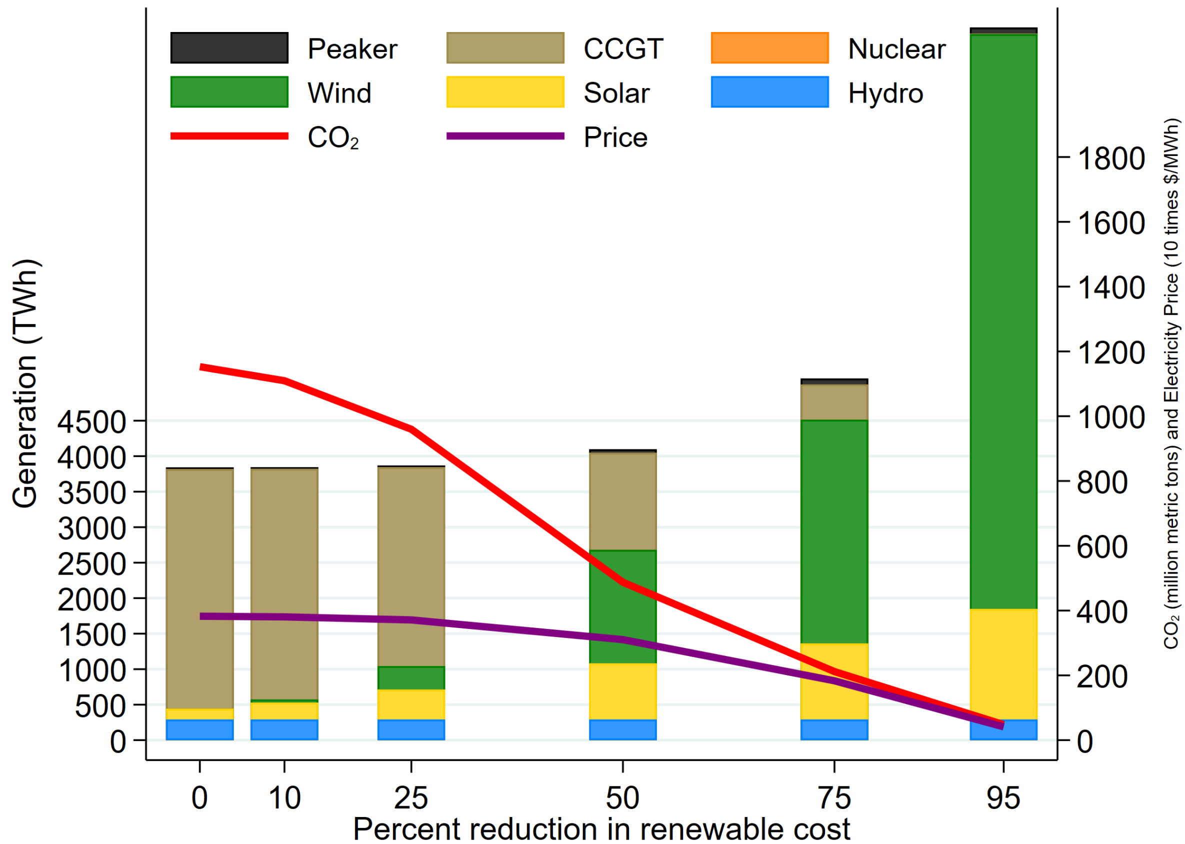


Figure A.6: Reduction in renewable generation capital costs (Iso-elastic demand).

Notes: Baseline parameterization with iso-elastic demand, no storage, and no interregional transmission aggregated across all regions.

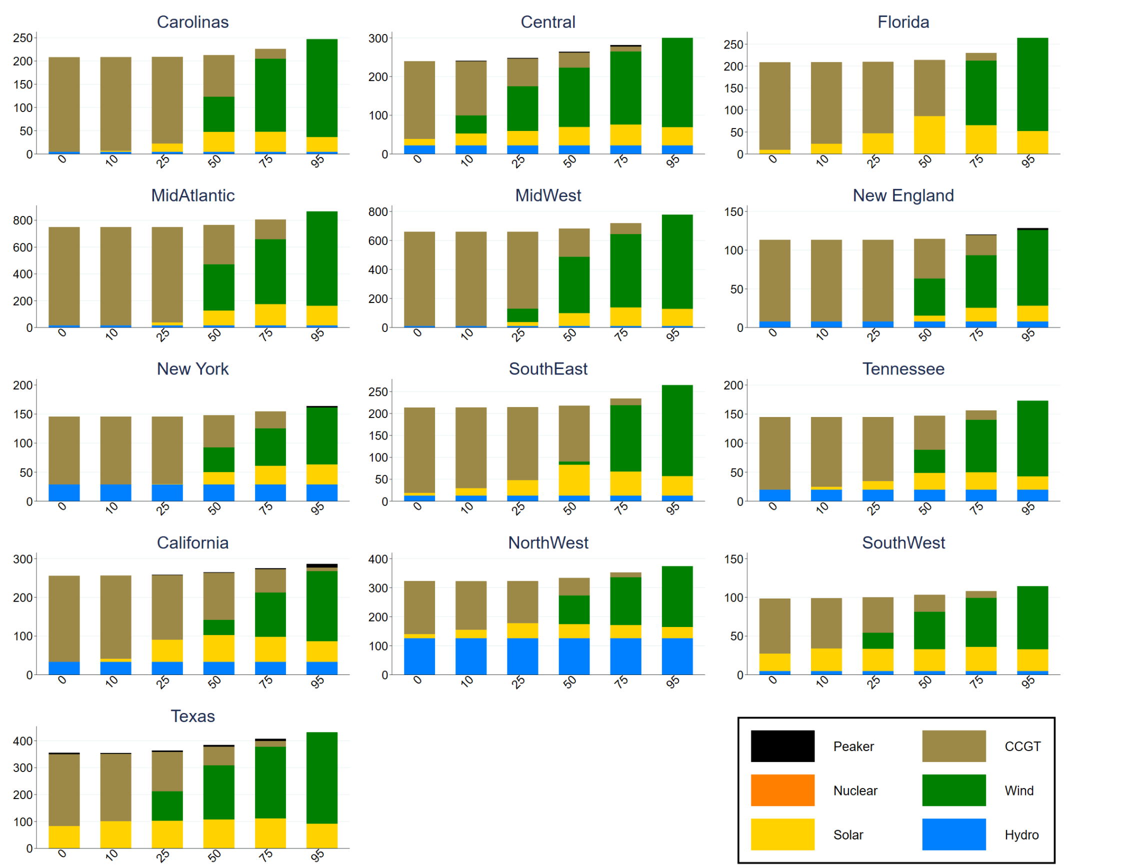


Figure A.7: Reduction in renewable generation capital costs for each region

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission.

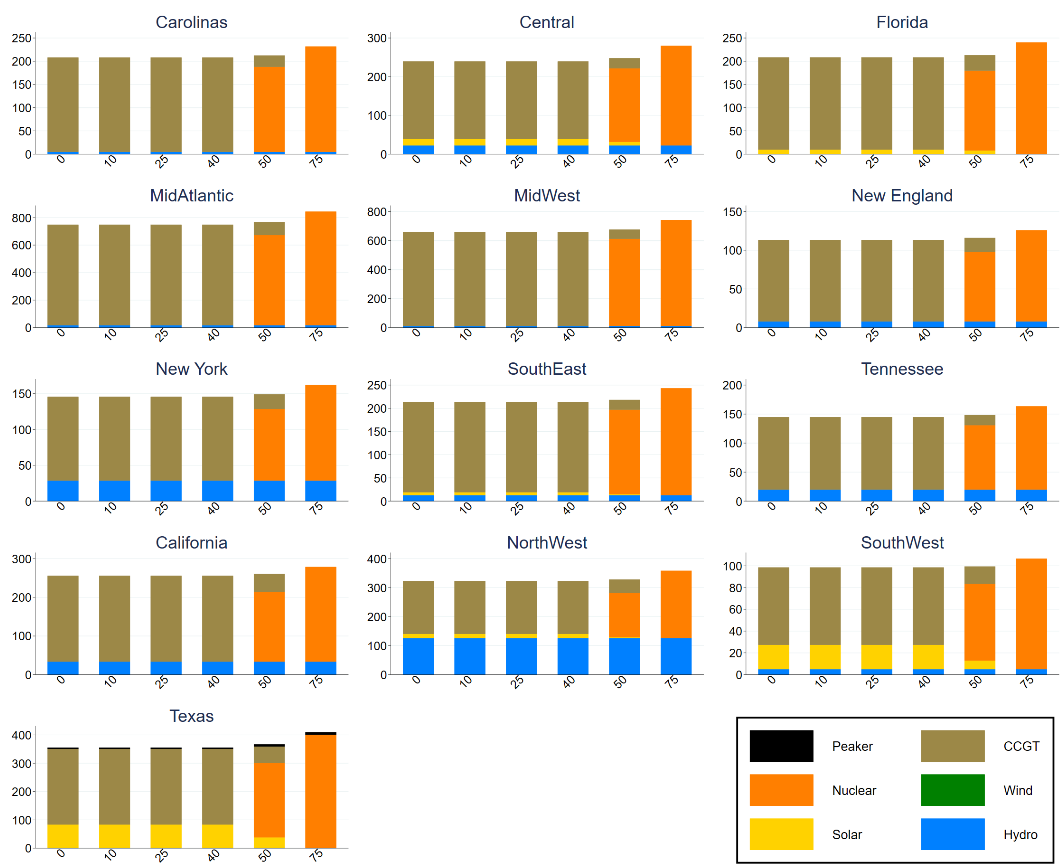
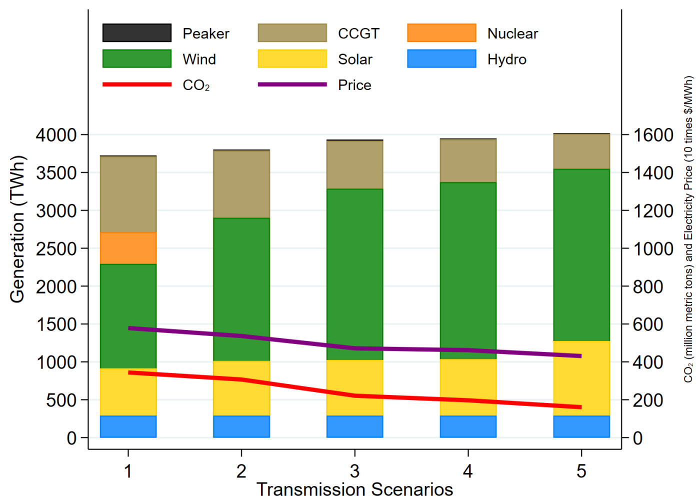
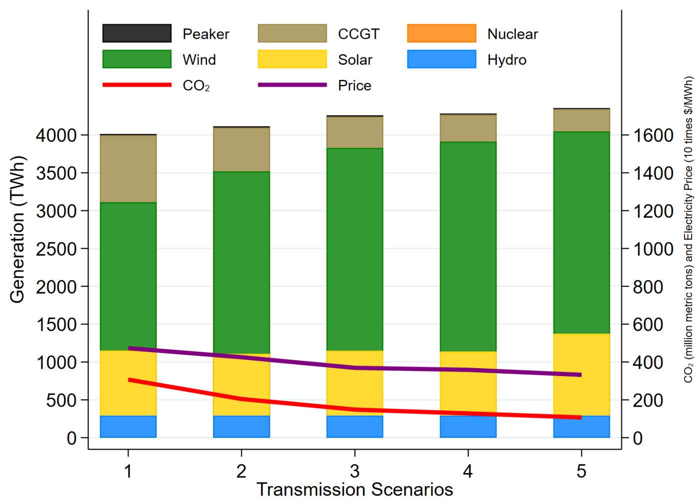


Figure A.8: Reduction in nuclear generation capital costs for each region (Linear demand)

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission.



(a) Baseline renewable capital costs.



(b) 25% reduction in renewable capital costs.

Figure A.9: First best transmission scenarios with SCC=100.

Notes: Baseline parameterization with iso-elastic demand and no storage. 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.

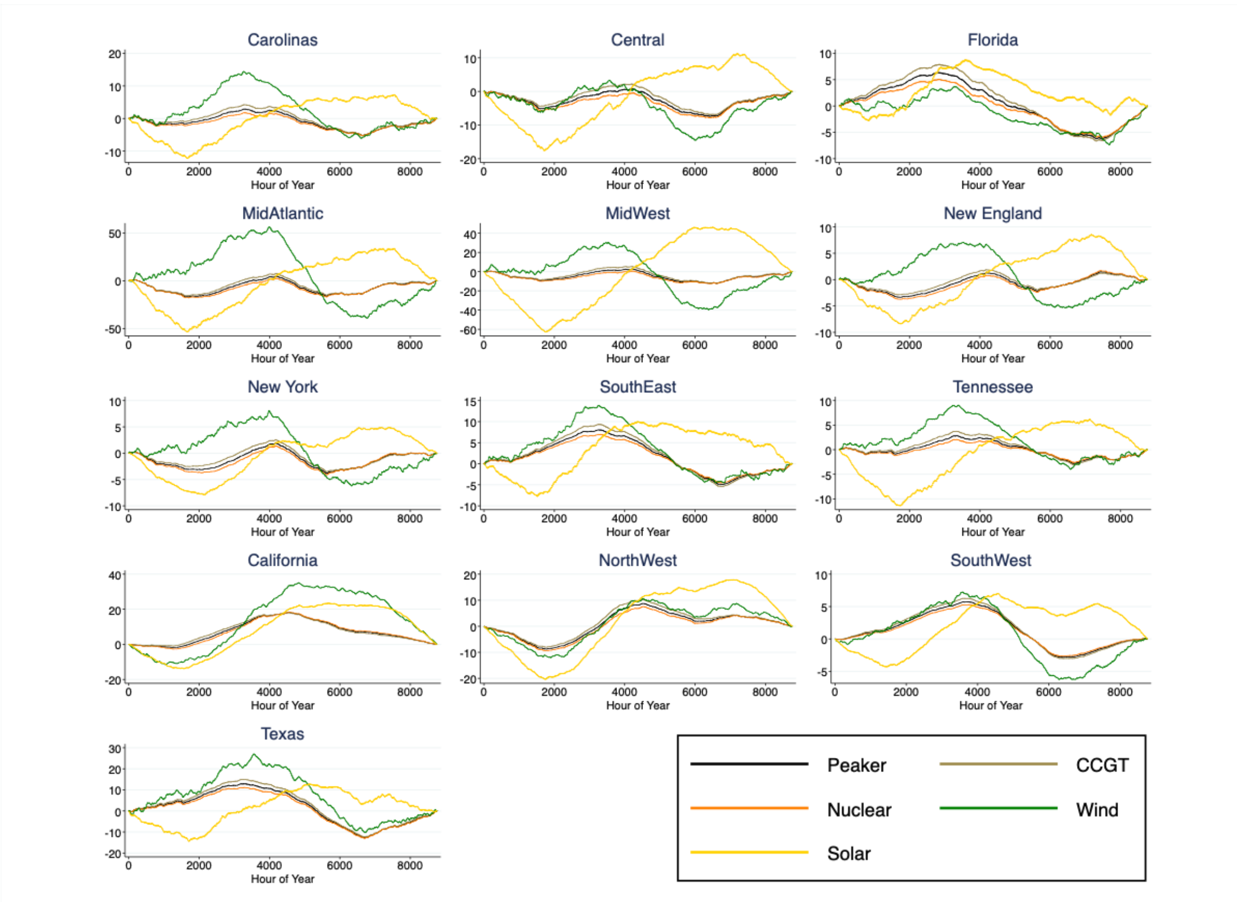


Figure A.10: Cumulative battery storage relative to Jan 1 for each region.
Notes: Assumes linear demand, free battery capacity, and a single generation technology. Required battery capacity is the range.

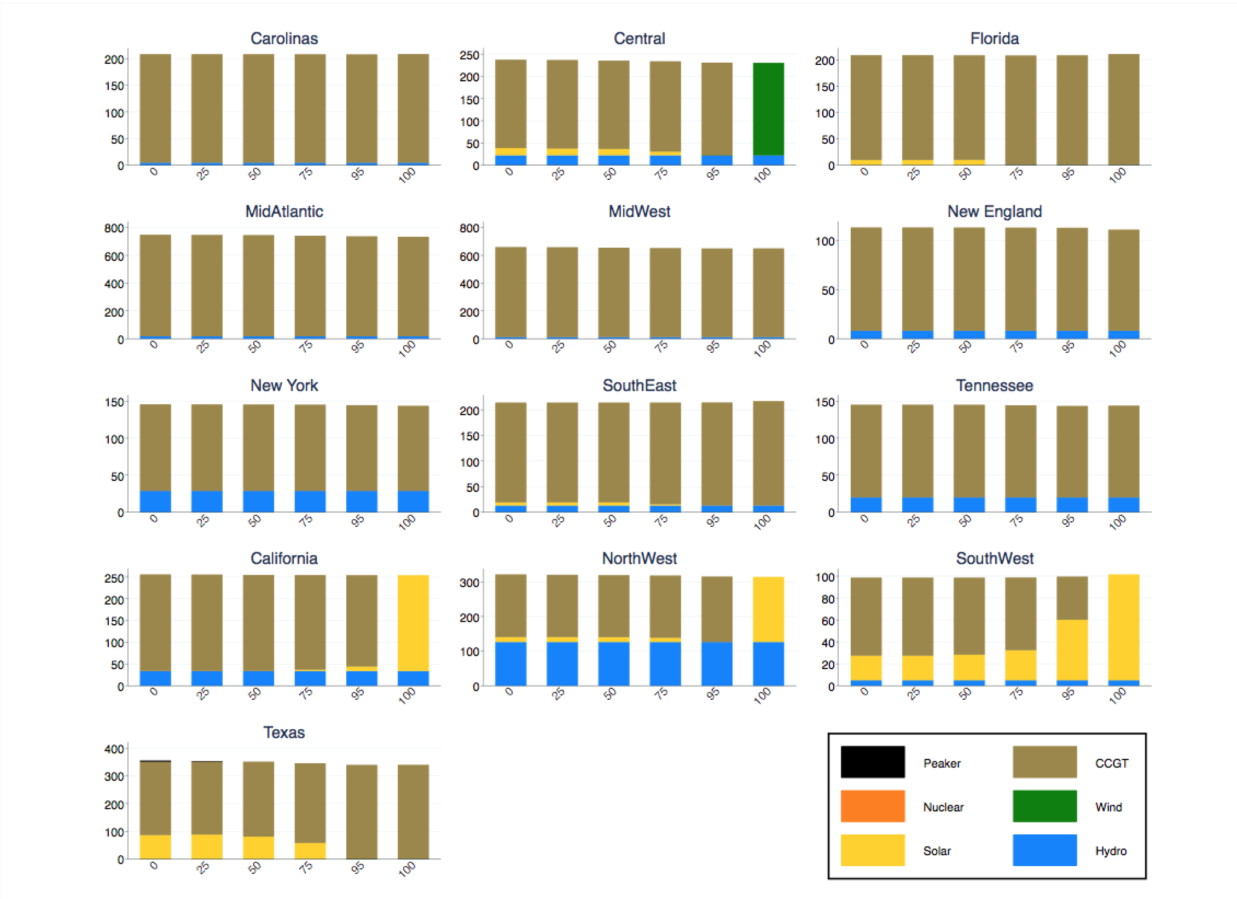


Figure A.11: Reduction in battery capital costs for each region

Notes: Baseline parameterization with linear demand and no interregional transmission. First bar has no battery, second bar has battery with baseline costs, third bar has battery with 25% reduction in capital costs, and so on.

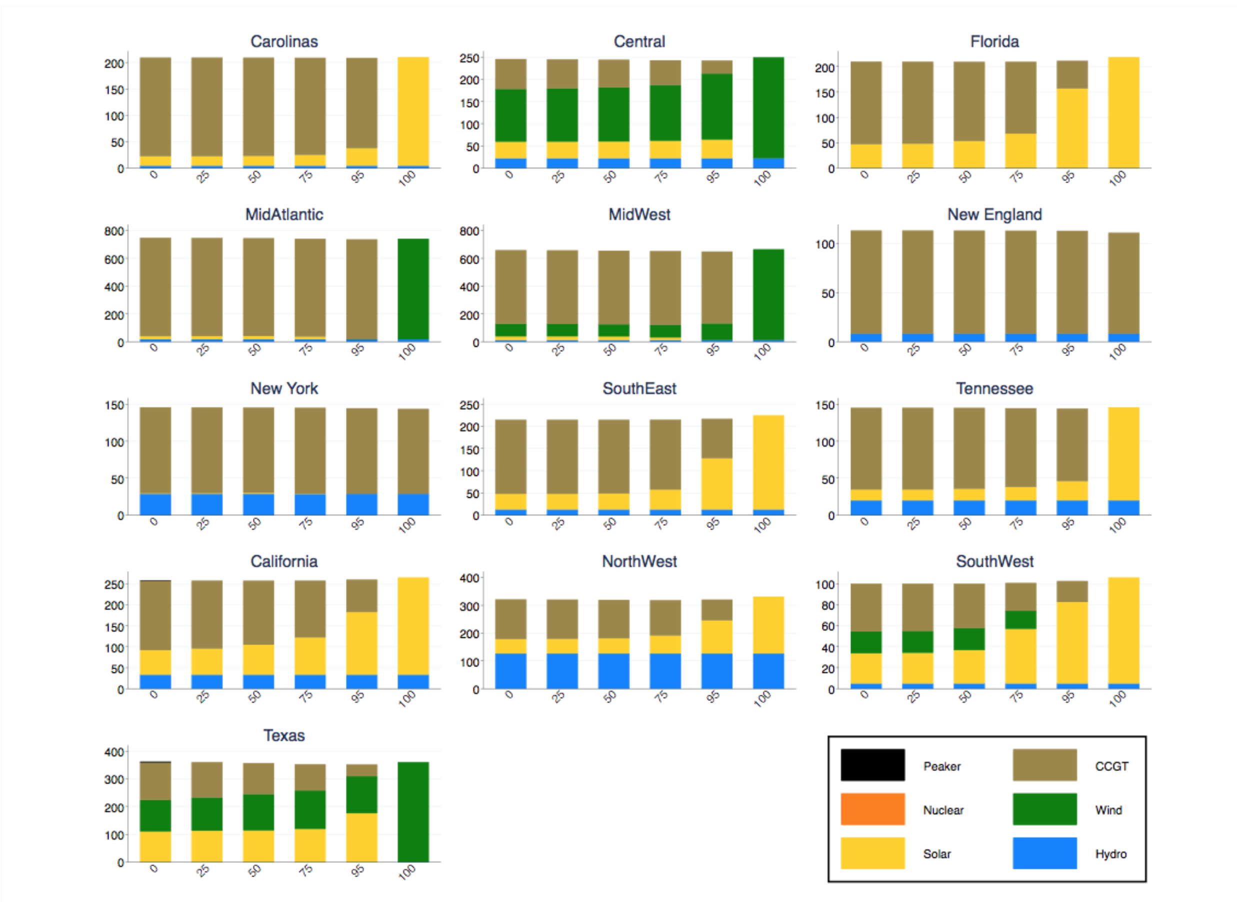


Figure A.12: Reduction in battery capital costs for each region (25% renewable capital cost reduction)

Notes: Linear demand, no interregional transmission, and 25% reduction in renewable capital costs. First bar has no battery, second bar has battery with baseline costs, third bar has battery with 25 % reduction in capital costs, and so on.

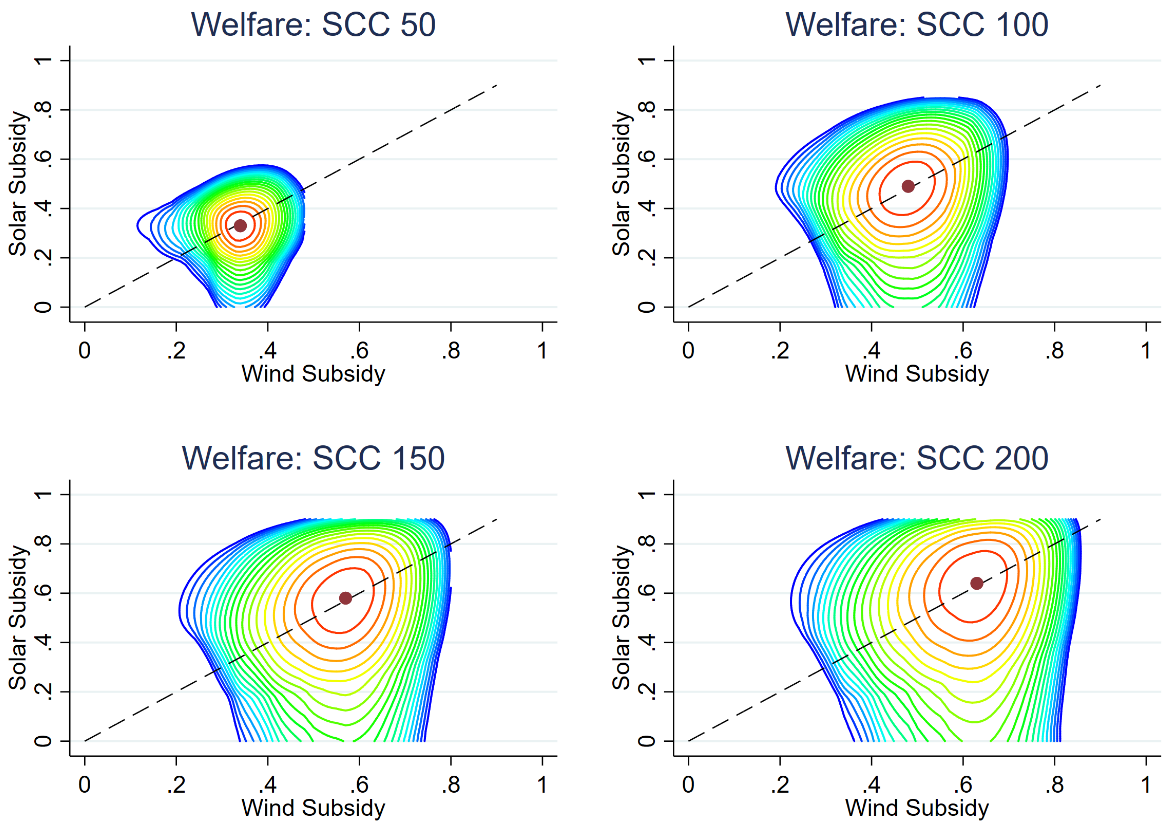


Figure A.13: Iso-Welfare curves as a function of wind and solar subsides
Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Red is the highest value for welfare and blue is the lowest. Illustrates the results in Table 4.

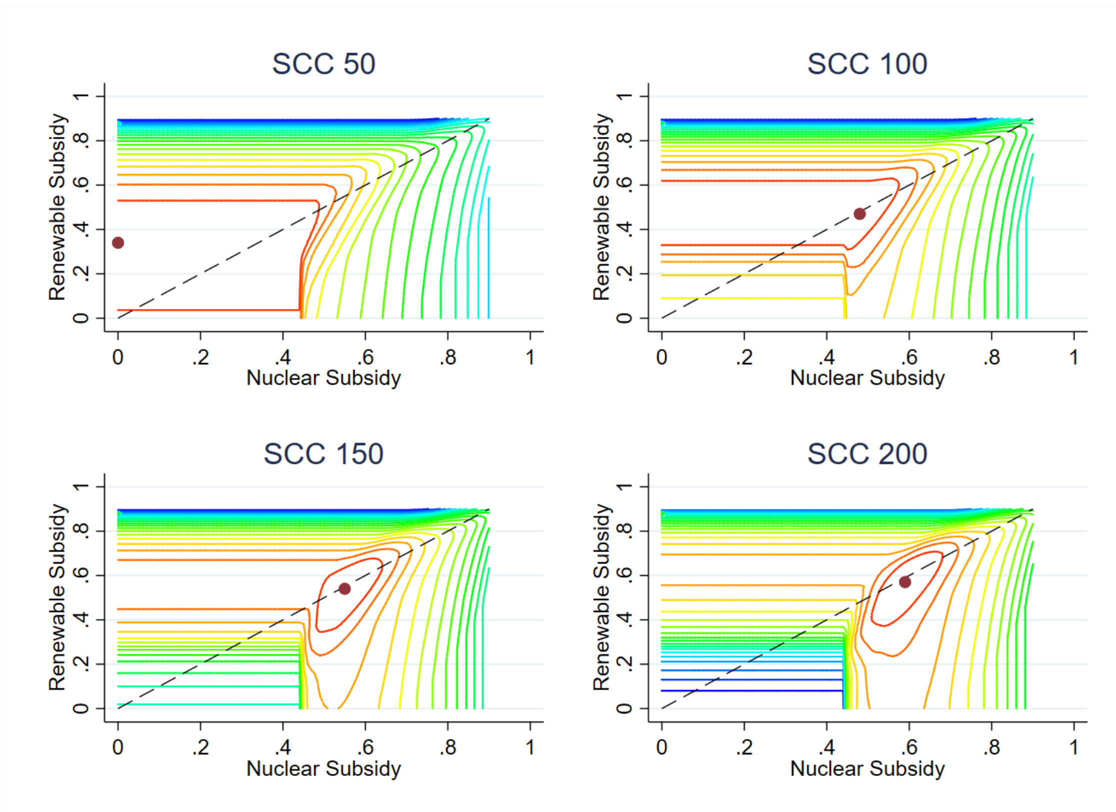
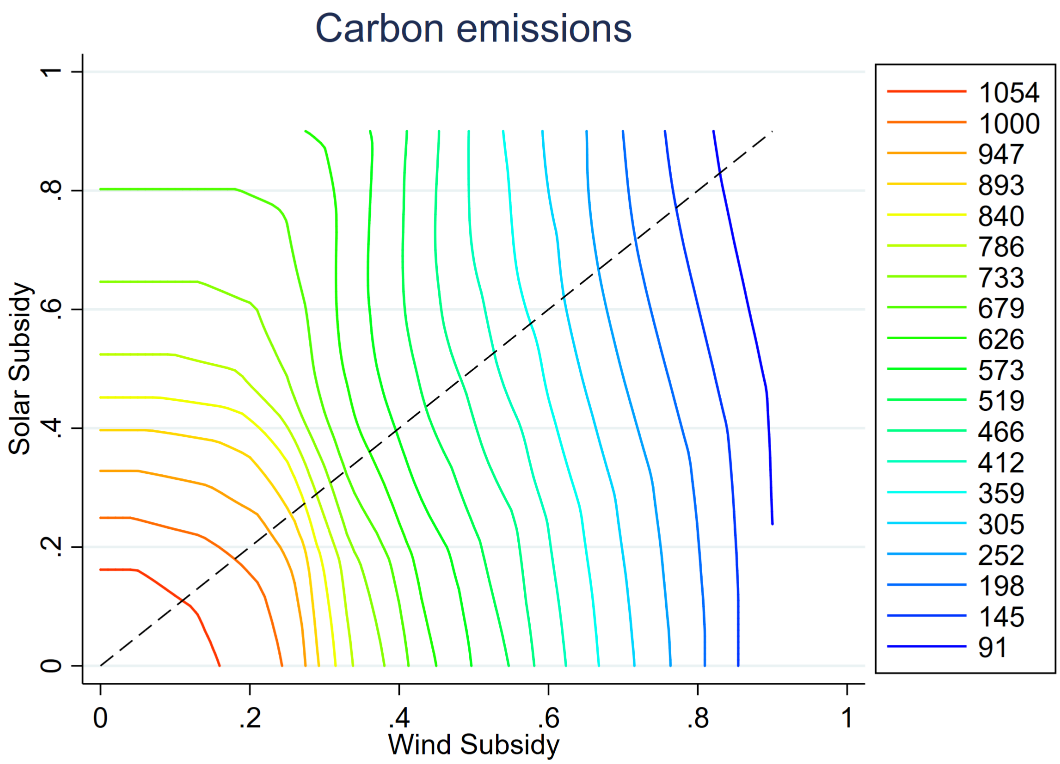
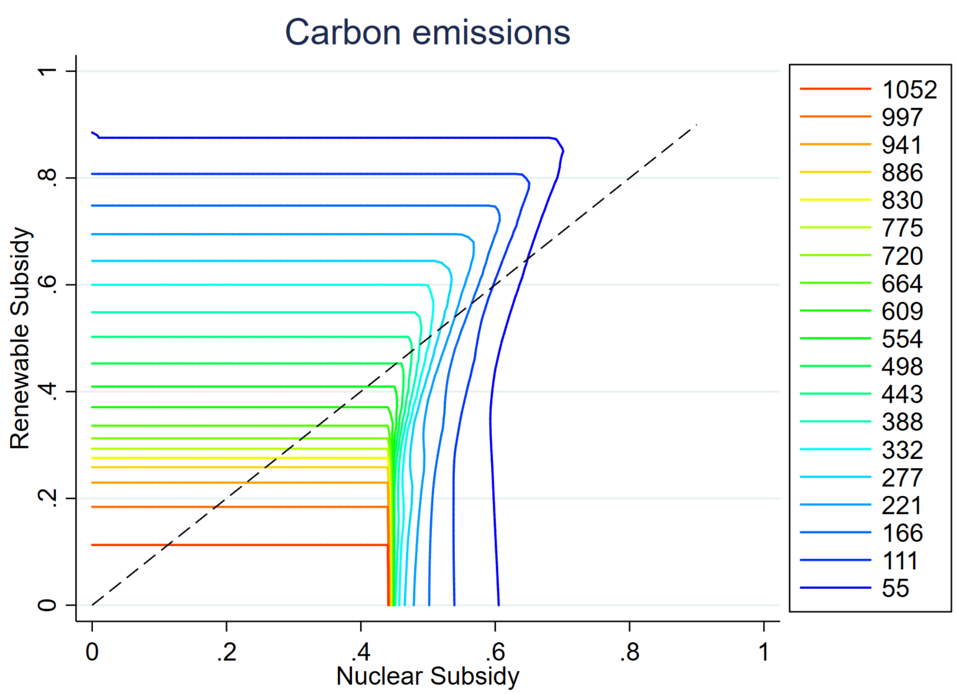


Figure A.14: Iso-Welfare curves as a function of nuclear and renewable subsides
Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Red is the highest value for welfare and blue is the lowest. Illustrates the results in Table 4.



(a) Carbon emissions as a function of wind and solar subsides



(b) Carbon emissions as a function of nuclear and renewable subsides

Figure A.15: Comparison of carbon emission contours

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. Illustrates the results in Table 4.

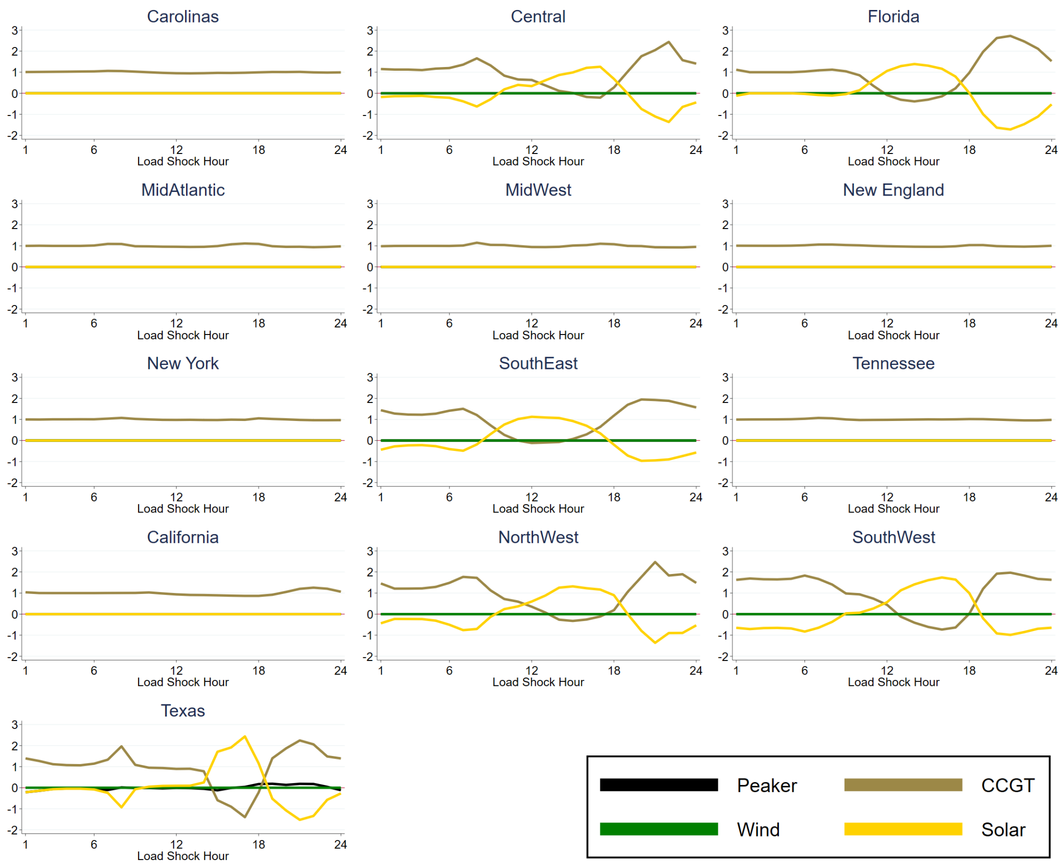


Figure A.16: Incremental generation from each technology by hour-of-day load shocks for each EIA region.

Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. 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.

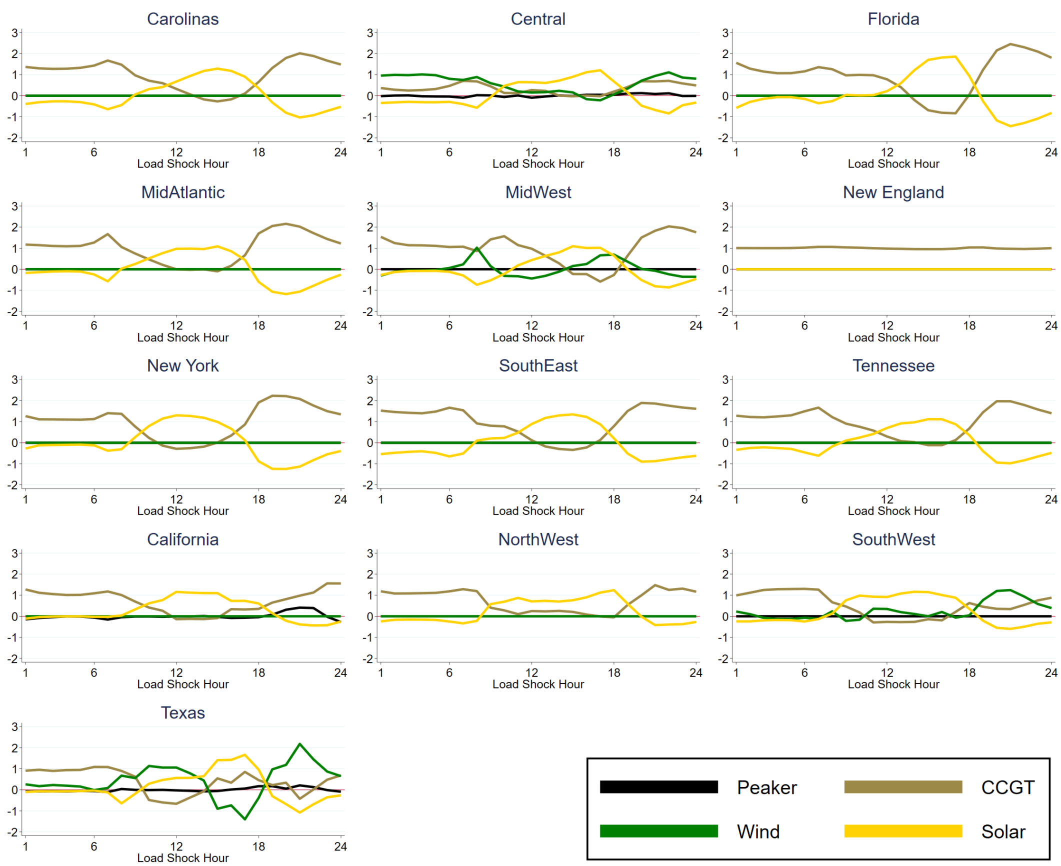


Figure A.17: Incremental generation from each technology by hour-of-day load shocks for each EIA region (25% renewable capital cost reduction).

Notes: Parameterization with linear demand, no storage, no interregional transmission, 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.

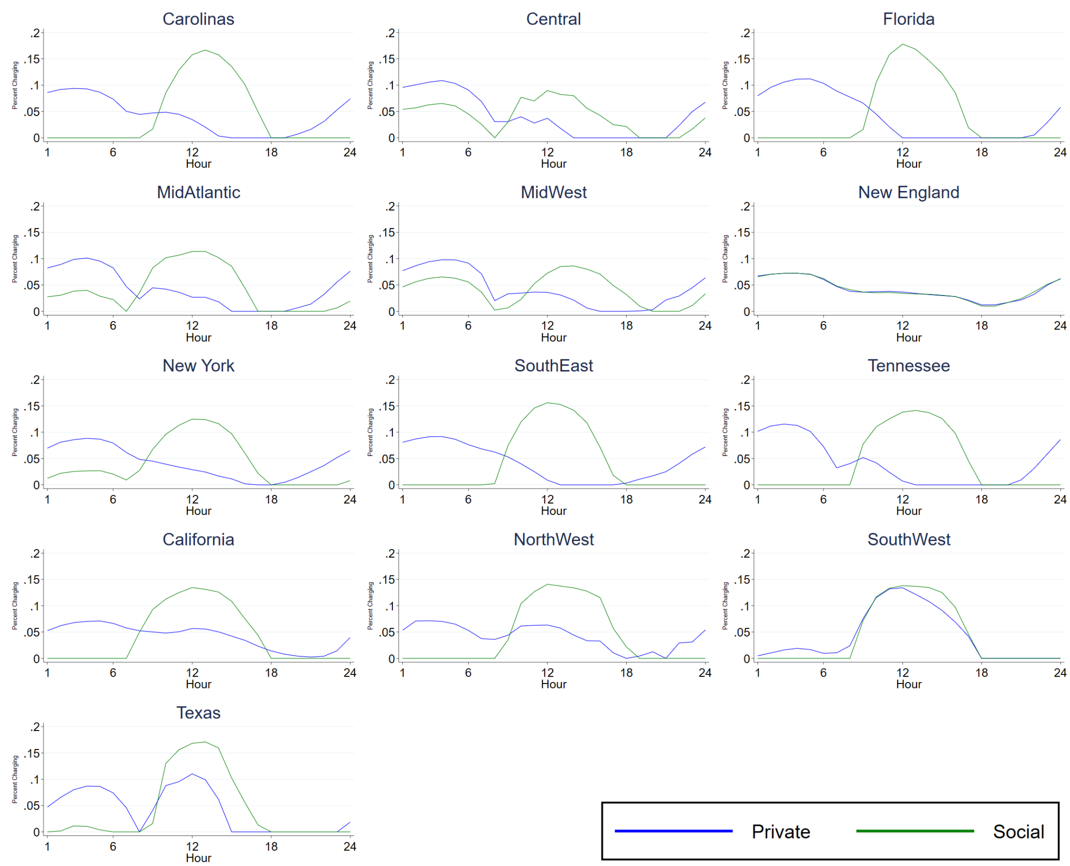


Figure A.18: Private and socially optimal EV charging profiles for each region.
Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. "Private" charging profile optimizes benefits assuming no carbon damages. "Social" charging profile optimizes benefits assuming the SCC is $100 per mt.

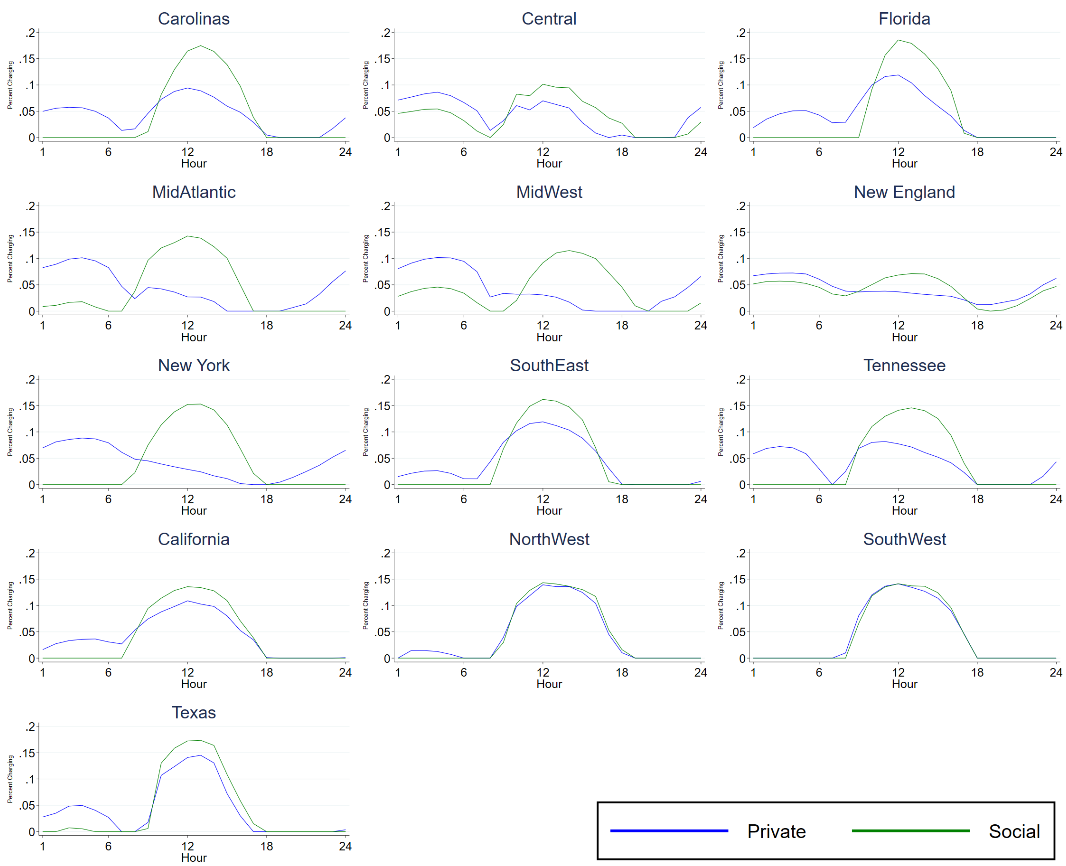


Figure A.19: Private and socially optimal EV charging profiles for each region (25% renewable capital cost reduction).
Notes: Baseline parameterization with linear demand, no storage, and no interregional transmission. "Private" charging profile optimizes benefits assuming no carbon damages. "Social" charging profile optimizes benefits assuming the SCC is \$100 per mt.