Electrification in the Long Run*

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

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Abstract

Electrification requires switching from fossil fuels to electricity to power transportation, heating, and industrial processes. We study electrification in a long-run model that captures crucial aspects of electricity markets including time-varying demand, intermittent renewables, and costly storage. Theoretical possibilities differ from short-run intuition. Electrification may crowd out renewable investment, or it may lead to *decreased* electricity-sector emissions, depending on the time profile of increased electricity usage. To analyze these possibilities we calibrate the model to the U.S. We calculate long-run emissions changes from electrification and show that electrifying vehicles could decrease total electricity emissions if vehicles charge during the day.

JEL Codes: H23, Q4, Q53, Q54

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†University of North Carolina at Greensboro and NBER. Email: sphollan@uncg.edu. Phone: 336-543-3851. Fax: 336-334-5580.

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

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

1 Introduction

Addressing climate change will require dramatic changes in many sectors of the economy including electrification of many direct uses of fossil fuels. Technological advances in batteries and electric drive-trains make possible the electrification of transportation, which currently accounts for over a third of carbon emissions. Similarly, advances in heat pumps open possibilities for electrification of space heating and some industrial processes.[1] However, electrification alone is not sufficient because addressing climate change also requires decarbonization of the electricity grid by investing in zero-carbon generation. In fact, there may be interconnected feedback effects such that electrification may help or hinder this investment. Developing policies to support electrification requires understanding these long term effects of electrification on investment in both fossil fuel and renewable electricity generating capacity and ultimately on emissions.

This paper constructs a framework for analyzing changes in electricity usage (e.g., electrification) in a long-run competitive equilibrium model of electricity consumption, generation, capacity investment, and storage.[2] Our focus on the long run, in which there are no legacy electricity plants, provides a unique framework to evaluate the interconnected feedback effects between electrification and investment.[3] The model captures realistic aspects of electricity and renewable generation: demand and renewable availability differ across locations and across hours, days, and seasons and their correlations influences investment. We use the model to derive several surprising theoretical possibilities from electrification. Calibrating the model to U.S. electricity markets allows us to assess the degree to which these possibilities have practical relevance and to evaluate the long-run environmental impacts of electrification across different regions, costs, and carbon policies.

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

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

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

Our model provides timely insight for policy analysis, policy implementation, and carbon accounting. In the absence of carbon pricing, climate policy currently focuses on a range of second-best subsidies to encourage electrification. For example, the Inflation Reduction Act (IRA) includes direct subsidies or tax credits for electric vehicle (EV) purchases, for EV charging station development, for hydrogen production, for renewable investment, for electricity storage, for energy efficiency, and for residential electrification. Designing optimal subsidies that change electricity use depends on assessing the environmental impacts. Policy implementation may also require calculations of environmental impacts. For example, the amount of the IRA hydrogen tax credit depends on the carbon emissions of the resulting hydrogen. Finally, carbon accounting quantifies the environmental impacts of electricity use. Technological advances in artificial intelligence may increase electricity consumption, and policies encouraging renewable generation may decrease net electricity consumption. Electricity using firms are increasingly aware of the environmental impacts of their electricity use and seek to offset environmental harm using carbon accounting. In each of these cases, understanding the interconnected feedback effects on investment is required for an accurate assessment of the environmental impacts.

We use our model to analyze the long-run effects of a change in electricity usage on generation, electricity prices, and, most importantly, emissions. We define the long-run emissions change (LREC, in tons per MWh) as the steady-state change in emissions normalized by the steady-state change in electricity demand.[4] The long-run effects can differ in surprising ways from their short-run analogs. In the short run, electrification (weakly) increases generation from renewables and increases electricity prices. Short-run environmental effects of electrification, sometimes called marginal emissions, must be between zero and the emissions rate of the dirtiest technology (adjusted for line losses). In the long run none of these effects necessarily hold.

[4] A large literature estimates short-run marginal emissions using either econometrics (Holland and Mansur (2008); Holland et al. (2016); Graff Zivin et al. (2014); Siler-Evans et al. (2012); Fell and Kaffine (2018)) or grid dispatch models (Raichur et al. (2015)). Holland et al. (2022) shows conditions under which short-run marginal emissions estimates can be used to analyze emissions over a 10-15 year time frame. A few papers (Hawkes (2014), Gagnon and Cole (2022)) directly study long-run marginal emissions using dispatch models. We do not use the term "marginal" in our definition of LREC because we consider both small and large changes in electricity usage.

Our theoretical analysis uses transparent special cases of the model to show the intuition for why short-run effects may break down in the long run. We show that electrification can induce entry which lowers some electricity prices and can *increase* total consumer surplus to existing consumers. In addition, electrification can *decrease* renewable generation, and LRECs from electrification can be negative or can exceed the emissions rate of the most polluting technology. Negative LRECs imply that electrification not only avoids direct emissions from the electrified sector but can also reduce emissions from the grid. Negative LRECs additionally imply that increased electricity consumption (for example from Bitcoin or data centers) might also have an environmental benefit. On the other hand, high LREC's would imply large harm from increased electricity consumption, and, depending on the avoided direct emissions, may even imply that electrification leads to a counterproductive increase in emissions. Finally, we show that cheaper renewables and higher carbon taxes can both *increase* LRECs from electrification.

We quantify these long-run effects by calibrating our model for five generating technologies and each of thirteen EIA electricity regions using observed hourly demand and corresponding hourly solar and wind generation for each hour of 2019.[5] Implicitly, we use observed data as draws from the complex, empirical joint distribution of shocks to demand as well as wind and solar availability. This provides realistic approximations of the underlying variation and correlations between demand and renewable availability for the entire contiguous U.S. In addition to wind and solar, our calibration includes nuclear power, two natural gas powered technologies, and battery storage.[6] Existing hydro power plants are cost effective but are difficult to expand so hydro power generation is fixed at historical levels. Cost estimates are for the near future, and we analyze a range of renewable capital costs, which are particularly uncertain. In our calculations, new coal plants are not constructed,

[5]Our calibration is distinguished in both scope and scale. Most analyses with national scope analyze a limited set of representative time periods (Gillingham et al. (2021), Palmer et al. (2011), Stock and Stuart (2021)) while analyses with richer demand and renewable representation focus on a single region or Independent System Operator (ISO) (Gowrisankaran et al. (2016), Elliot (2021), Imelda et al. (2018)).

[6]Battery storage has been widely studied but is computationally intensive so most studies focus on a single region. See Karaduman (2020), Butters et al. (2021), Junge et al. (2021), and Shrader et al. (2021). See Andres-Cerezo and Fabra (2022) for an analysis of storage and market power.

because they are dominated by natural gas plants.[7] Because we are analyzing the long-run steady state and not a transition path, we do not model any existing plants.[8]

Using the calibrated model, we conduct simulations based on four scenarios: low- and high-cost renewables with and without Pigouvian carbon pricing. We begin by analyzing small electrification shocks at each hour of the day and find a wide range of outcomes consistent with our theoretical results. For some regions and hours, electrification increases capacity in fossil generation which crowds out renewables. This can result in LRECs higher than the emissions rates of natural gas peaker plants. In other cases, electrification expands renewables, crowds out fossil, and results in negative LRECs. For the scenario with high-cost renewables and carbon pricing, electrification can crowd out or crowd in nuclear capacity resulting in LRECs which can be very high or negative.

We next analyze small-scale electrification use profiles, e.g., at night, in winter, or during summer days.[9] For example, our winter electrification profile would be appropriate for heat pump adoption; the summer day profile for increased air conditioning; the daytime profile for commercial electricity uses that operate during the day; and a flat profile for 24-by-7 electricity uses. We find substantial heterogeneity in LRECs across regions and profiles, ranging from large positives to substantial negatives. Pigouvian carbon pricing and, to a lesser extent, low cost renewables reduce the range of LRECs but substantial heterogeneity remains. In general we find lower LRECs in the daytime (compared to nighttime) and in the summer (compared to winter) driven primarily by how electrification timing affects solar investment.

Although many electricity uses occur at fixed times, some electricity usage is more flexible. For example, electric vehicles (EVs) use batteries to store electricity, and the batteries can be charged at different times of day. In particular, smart charging can increase charging flexibility and allow EVs to be charged to meet different objectives. We analyze electrification of the entire light-duty vehicle fleet under five different charging profiles: one profile is based

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

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

[9] For analysis of the short-run effects of the timing of electrification and energy efficiency investments see Boomhower and Davis (2020).

on observed charging behavior (presumably convenient charging times), one profile assumes all hours are equally likely, and three profiles are optimized to minimize carbon emissions, maximize social welfare, and minimize charging costs.

In all scenarios, electrification of the light-duty vehicle fleet reduces transportation carbon emissions, but may or may not reduce electricity sector emissions depending on the charging profile.[10] In the absence of carbon pricing, we find large *negative* LRECs for many regions under carbon minimizing or socially optimal charging. Remarkably, negative LRECs imply that charging EVs with these profiles can completely decarbonize passenger vehicle transportation *and* can reduce carbon emissions from the electricity sector, because charging induces entry of renewables and crowds out fossil generation. However, there is substantial disagreement between the timing of socially optimal and cost minimizing charging. Because individuals will likely charge during low cost or convenient hours, this implies that EV adoption likely will increase electricity sector carbon emissions in the absence of policy targeting the timing of charging. With carbon pricing, the range of LRECs narrows across profiles and across regions, and socially optimal charging and cost minimizing charging are quite similar. This aligns private and social charging incentives, provided that EV owners face time-varying electricity prices, as they do in our model. Substantial heterogeneity remains in LRECs across regions and charging profiles even with Pigouvian carbon pricing.

EV charging will depend partially 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 generally result in much lower LRECs than charging stations that facilitate charging at night (*e.g.,* at apartment buildings and on-street parking locations). There are exceptions to this general rule, however. In some regions, charging during the day may induce entry of solar which crowds out nuclear investment and generation and hence raises emissions. This highlights the importance of locational and temporal heterogeneity in electrification policy and of investment incentives; factors which our framework is well suited to analyze.

[10]Holland et al. (2022) use short-run marginal emissions to estimate that about half the emissions reduced in the transportation sector from partial electrification would be offset by increased electricity sector emissions given today's grid.

Complementing these results on electrification and EV adoption, we make three additional contributions. One contribution of our paper is the transparency, tractability, and flexibility of our long run model. This allows us to develop simple theoretical insights and clearly illustrate the intuition driving the results. Second, our modeling framework allows welfare and distributional analysis. Many existing models of the electricity sector only model cost minimization and do not analyze gains or losses from changes in electricity consumption. Finally our modeling framework can be used to analyze decarbonization policy more broadly. In ongoing research Holland et al. (2022), we use our model to study the effects of decarbonization policies such as carbon taxation and subsidies for (or technological innovation in) renewable generation, storage, nuclear power, and transmission.[11] Our framework focusing on the long-run steady state provides a unique alternative and valuable complement to existing methodologies which focus on the transition path of investment.

2 The model

sec-model

Consider a long-run model in which electricity consumption, generation, storage, and generation capacity are all endogenous. Because electricity demand and renewable availability vary across time, we model a long-run competitive equilibrium with T periods, (*e.g.,* hours) in which all agents have perfect foresight. In a given period t, electricity consumption by existing consumers is Q_t, and their hourly benefit (gross consumer surplus) is $U_t(Q_t)$ where $U_t' > 0$ and $U_t'' < 0$. The demand function, D_t, is the inverse function of U_t' defined by $U_t'(D_t(p)) \equiv p$.[12] Additionally, let $\bar{E}_t \geq 0$ be the electricity consumption of an activity that switches from fossil fuels to electricity. Because we consider a wide variety of such activities, we assume $\bar{E}_t$ is exogenous to avoid taking a stand on the change in consumer surplus when the activity moves from fossil fuels to electricity.

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

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

Electricity can be generated from I different technologies, each of which produces electricity at a constant operating cost up to some limit based on the installed capacity. Let K_i 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).[13] Let c_i be the constant operating cost for technology i where the technologies are ordered such that $c_i \leq c_{i+1}$. Each technology may or may not have external costs, *e.g.,* carbon emissions, associated with its use. Accordingly, define $\beta_i \geq 0$ as the carbon emissions intensity of technology i.

Electricity may be transferred across time using a storage technology, e.g., a rechargeable 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 $S_t = S_{t-1} + b_t$.[14] Battery storage cannot exceed the maximum battery capacity K_s, so the state of the battery must satisfy $0 \leq S_t \leq K_s$. The battery capacity is endogenous in the model and has capital costs r_s per unit. Electricity balance in each hour requires that $Q_t + \bar{E}_t + b_t \leq \sum_i q_{it}$, i.e., total 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:

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

subject to all the constraints. This is a straightforward constrained optimization problem, albeit with a large number of choice variables.[15] To characterize the optimum, we use the pseudo-Hamiltonian, H_t, to write the Lagrangian, $\mathcal{L}$, for (1) as:

$$\mathcal{L} \equiv \sum_t H_t - \sum_i r_i K_i - r_s K_s. \tag{2}$$ eq:ObjL

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

[14] 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.

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

Here H_t is defined by:

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

where p_t, λ_{it}, ϕ_t, and μ_t are all non-negative shadow values of the relevant constraints.[16]

The Kuhn-Tucker first-order conditions include

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

$$q_{it} \geq 0 \qquad d\mathcal{L}/dq_{it} = -c_i + p_t - \lambda_{it} \leq 0 \qquad \forall i,t \qquad C.S. \qquad (4) \quad \texttt{eq:FOCq}$$

$$d\mathcal{L}/db_t = -p_t + \phi_t = 0 \qquad \forall t \qquad (5) \quad \texttt{eq:FOCb}$$

$$S_t \geq 0 \qquad d\mathcal{L}/dS_t = \phi_{t+1} - \phi_t - \mu_t \leq 0 \qquad \forall t \qquad C.S. \qquad (6) \quad \texttt{eq:FOCS}$$

$$K_i \geq 0 \qquad d\mathcal{L}/dK_i = \sum_t \lambda_{it} f_{it} - r_i \leq 0 \qquad \forall i \qquad C.S. \qquad (7) \quad \texttt{eq:FOCK}$$

$$K_s \geq 0 \qquad d\mathcal{L}/dK_s = \sum_t \mu_t - r_s \leq 0 \qquad C.S., \qquad (8) \quad \texttt{eq:FOCbarS}$$

where $C.S.$ indicates a complementary slackness condition.[17] If electricity consumption is positive, then (3) implies that $U_t'(Q_t) = p_t$, i.e., that the marginal benefit equals the shadow value p_t, so from here on p_t is simply called the *electricity price*.

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

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

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

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

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

[16] H_t is not technically the Hamiltonian of (1) because it treats the adjoint variable differently.
[17] Additional conditions are the constraints and their complementary slackness conditions.

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

The third lemma characterizes the optimal battery usage.

em:battery **Lemma 3.** *If $S_t = 0$, then $p_t \geq p_{t+1}$. If $0 < S_t < K_s$, then $p_t = p_{t+1}$. If $S_t = K_s$, 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.

The last lemma characterizes the relationship between equilibrium prices and equilibrium capacities.

rop:profit **Lemma 4.** *The first-order conditions imply that $\sum_t (p_t - c_i) q_{it} = r_i K_i$ for each technology i and $\sum_t -p_t b_t = r_s K_s$ for the battery.*

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 these lemmas, captures the essential features of electricity markets in an analytically tractable way. In Online Appendix Section O.A.1 we briefly discuss extensions to the model that account for other aspects of electricity markets such as ramping constraints and upward sloping supply curves for inputs to renewable generation. In the absence of market failures, the equilibrium is efficient. To extend the model to analyze the inefficiency from a carbon emissions externality, we define *private surplus* as the optimized value of [1] and *welfare* as the private surplus minus the damages from pollution plus net government revenue from any carbon tax policy. Note that under a carbon tax τ the operating cost of fossil generation is $c_i + \beta_i \tau$. These definitions enable us to analyze the long-run welfare effects.

We define *electrification* in the long run as an increase (typically from zero) of $\Delta \bar{E}_t$ for some t, where Δ is the difference operator. Except for edge effects at the choke price, an increase in hour t is equivalent to a horizontal shift in the demand curve D_t by an amount equal to $\Delta \bar{E}_t$. Note that in the context of our model, the electrification is sustained and predictable, i.e., a steady state increase in electricity use in period t. We define the *long run*

emissions change (LREC) from electrification as the increase in emissions normalized by the increase in electricity consumption:

$$\text{LREC} = \frac{\sum_i \sum_t \beta_i \Delta q_{it}}{\sum_t \Delta \bar{E}_t}. \tag{9}$$ eq:LREC

This LREC is the difference in emissions (per unit of electrification) across two long run equilibria one of which has the steady state increase in electricity use.

In the short run in which capacities are fixed, electrification effects are straightforward: electricity usage and prices increase. Short-run environmental effects, sometimes called marginal emissions, are similarly intuitive: bounded above by the emissions rate of the dirtiest technology and bounded below by the emissions rate of the cleanest technology (typically zero). None of these necessarily hold in the long run. The following results illustrate some of the counter-intuitive possibilities.

The first result shows that long-run electrification can *decrease* emissions.

res:Dload **Result 1.** *Electrification can decrease carbon emissions, i.e., the LREC can be negative.*

Electrification 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 clean, its entry may meet the increased demand and offset emissions in other periods, thereby decreasing emissions. Figure 1 illustrates the proof. The figure models two time periods and two generating technologies: technology 1 is renewable with zero operating costs and technology 2 is fossil with positive operating costs c_2. In the initial equilibrium, the low demand period has only renewable generation and the high demand period has both renewable and fossil generation. The equilibrium prices are completely determined by the technologies' costs.[18] If electrification increases demand in the low demand period as shown, equilibrium prices do not change, so renewables enter such that p_l is unchanged. But because the renewable generation is available in both periods, the renewable entry leads to exit of fossil capacity. Fossil generation

[18]From Lemma 4, we have $p_l + p_h = r_1$ (revenue from renewable generation covers renewable capital costs) and $p_h = r_2 + c_2$ (revenue from fossil generation covers fossil capital and generation costs).

in the high demand period decreases, and that reduces carbon emissions so the LREC is negative.

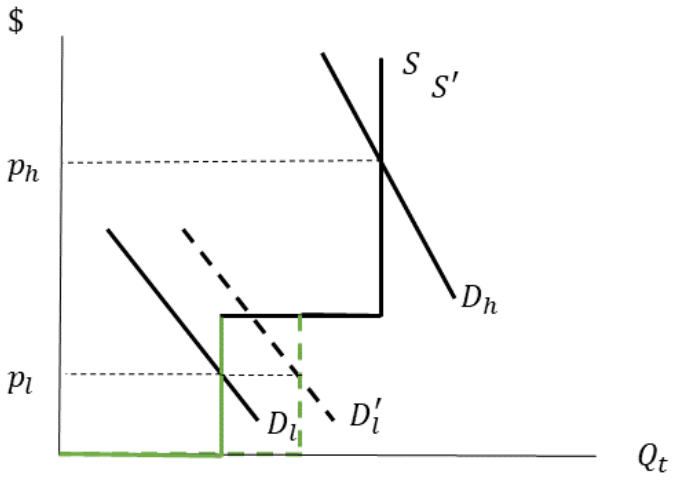


Figure 1: Illustration of Result 1.

Notes: Two periods: h and l, and two technologies: renewable (1, green) and fossil (2, black). Electrification in period l decreases emissions.

Of course, the LREC can be positive. If the marginal technology is fossil, carbon emissions increase, in line with short-run intuition. For example, if electrification were to increase demand in the high demand period in Figure 1, the LREC would be positive and equal to the emissions rate of the fossil technology.

In Figure 1, electrification in the low demand period leads to additional renewable capacity. However, electrification can *decrease* renewable capacity:

Result 2. *Electrification can decrease renewable capacity, which implies the LREC can be higher than* $\max_i\{\beta_i\}$.

Graphical illustrations of this result and all subsequent results are given in the Online Appendix Figures O.A.2 to O.A.6. To understand the intuition of the result, consider electrification that occurs in a period in which a dispatchable technology sets the price. This induces entry of the dispatchable technology to equilibrate price in that period. But that extra capacity will be available in other periods, which may crowd out renewables. If the dispatchable generation has carbon emissions, then the LREC is greater than the emissions rate of the dispatchable generation. For the two-period example in Online Appendix Figures O.A.2, the LREC is twice the emissions rate of the dispatchable generation.

In the short run, electrification increases prices, which harms existing consumers. This may be reversed in the long run.

res:CS **Result 3.** *Electrification can increase consumer surplus of existing consumers.*

Intuitively, electrification in one period potentially increases the price in that period. But this higher price induces entry of the technology on the margin in that period, which drives down prices in other periods. On net, the benefits to existing customers of lower prices in some periods may outweigh the cost of higher prices in other periods.

Next consider the effect of a change in the capital costs of renewables.

res:renew **Result 4.** *If the capital cost of renewables decreases, then carbon emissions can increase. The LREC with low renewable capital costs can be higher than the LREC with high renewable capital costs.*

Intuitively, 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 crowds out a low operating cost, zero-emission technology (such as nuclear) and increases the capacity of a polluting technology.

The final two results analyze storage costs and carbon taxes.

res:Store **Result 5.** *If storage becomes cheaper, then renewable capacity can decrease.*

Although conventional wisdom suggests that cheaper batteries will encourage greater renewable penetration, Result 5 shows that this is not necessarily the case.[19] If intermittent renewables generate electricity in high-price periods, then storage will reduce their profitability.[20]

res:Ctax **Result 6.** *If carbon taxes increase, $\Delta\tau > 0$, then emissions decrease, $\sum_i \sum_t \beta_i \Delta q_{it} < 0$, but total electricity consumption can increase i.e., $\sum_t \Delta Q_t > 0$. The LREC with carbon taxation can be higher than the LREC without carbon taxation.*

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

[20] Implicitly the storage 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.

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. To see how the LREC can be higher with carbon taxation, recall that Result 1 shows that the LREC can be negative if it causes renewables to crowd out a fossil technology. Consider this the case without carbon taxation. Now suppose that carbon taxation drives the fossil technology out of the equilibrium, and hence there is only the renewable technology. In this case the LREC is zero, and hence the LREC is higher with carbon taxation that without it.

Results 1 to 6 show that the long-run effects of electrification can differ in surprising ways from their short run analogs. We next assess the empirical relevance of these results with a realistic calibration of the model.

3 Model calibration and solution algorithm

We calibrate our model for a representative year, 2019, based on 8760 observations of hourly electricity consumption and availability of generation from solar and wind for each of thirteen EIA electricity regions (Figure 2).[21] Using observed 2019 consumption and renewable availability provides a realistic approximation of the underlying structural correlations between electricity consumption and renewable availability both over time and over geographic locations. We consider each EIA region to be independent to capture geographic variation in demand and renewable availability.

3.1 Demand calibration

Modeling hourly demand in each electricity region requires assumptions about functional forms and data on observed prices and quantities. We assume linear demand in each hour

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

that is independent of demand in other hours. 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.[22]

Observed hourly electricity consumption is collected from EIA Form 930 (USEIA 2019a) and is the total of load from all reporting entities within the EIA region for that hour. The mean observed consumption by season and hour of day is shown in Figure O.A.7 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 use hourly market prices for each ISO from SNL (2019). These prices are weighted averages of real-time single bus prices or aggregated regional hub prices. For prices in the regions not in organized markets, we use system lambdas from FERC Form 714 (FERC 2019) as a proxy. The mean hourly price by season and hour of day is shown in Figure O.A.8, and summary statistics are in Table O.A.1. The observed consumption and prices show substantial variation across hours, seasons, and regions which we assume is representative of underlying structural demand conditions.

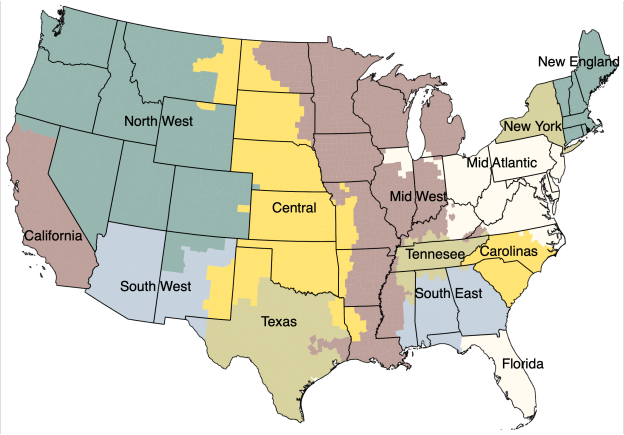


Figure 2: Map of EIA regions.

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[22]In reality, electricity demand is a complicated relationship between electricity usage across hours and a large vector of hourly electricity prices. In addition, electricity pricing is subject to a variety of distortions so that most consumers' prices are not the hourly social marginal cost. Here we focus on the carbon market externality and leave analysis of additional distortions to future work.

3.2 Capital costs, operating costs, and emissions

We consider five generation technologies: solar photovoltaic (PV), wind, nuclear, combined cycle gas, and combustion turbine (peaker) gas. Operating and capital costs from USEIA (2021) are shown in Table 1 for the five technologies and for grid-scale battery storage. Operating cost, c_i, is primarily fuel costs for the natural gas technologies. 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.

Table 1: Operating Costs, Capital Costs, and Emissions for Different Technologies

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

Notes: Source USEIA (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)". "Operating Cost" is the levelized variable cost from Table 1b. "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. All dollar amounts in the paper are in 2020 dollars.
* Capital cost of battery storage is in MWh.

Solar and wind are both renewable and have zero operating costs and zero emissions but are intermittent. USEIA (2021) shows that capital costs of renewables have declined dramatically from 2014 to 2021, and projections to 2050 suggest large future declines for capital costs of solar and storage. Because of the speculative nature of these distant forecasts, we consider High and Low Cost cases where the Low Cost case has capital costs of renewables 25 percent below those shown in Table 1.

To determine hourly capacity factors for the intermittent renewables, we divide observed hourly renewable generation reported in EIA Form 930 (USEIA 2019a) by a measure of renewable capacity. Renewable capacity is not reported in the EIA 930 and is increasing

rapidly throughout 2019. We account for this by using the following procedure. For each region, we aggregate monthly renewable generation from EIA Form 923 (USEIA 2019b) and monthly renewable capacity from EIA Form 860 (USEIA 2019c) across all plants which are built after 2010 and which report to both datasets.[23] Dividing these gives region-month capacity factors for wind and solar. We then divide the mean EIA 930 hourly generation for each region and month by these region-month capacity factors to calculate region-month capacities appropriate for EIA 930. Dividing EIA 930 hourly generation by the region-month capacities gives our hourly capacity factors. Figure O.A.9 shows mean hourly capacity factors by season and hour of day for each region, and summary statistics are in Table O.A.1. The capacity factors show seasonal and hourly patterns which are consistent with estimates of renewable availability. We also include renewable hydropower by holding hourly generation from hydropower exogenously fixed at 2019 levels.

The non-renewable technologies in Table 1 are all dispatchable. Compared to renewables, advanced nuclear also has zero emissions but has slightly higher operating costs and much higher capital costs. Nuclear may appear to be dominated by renewables based on these costs, but because of renewables' intermittency, an equilibrium may have positive capacities of both nuclear and renewables. The two natural gas technologies have the highest operating costs and positive emissions rates. Combined cycle gas plants have lower operating costs and emissions but higher capital costs than peaker gas plants. Peaker gas plants have the highest operating costs and emissions rates of any generation technology, but have the lowest capital costs, so they can potentially recover capital costs by operating only during a few hours of peak demand.

Carbon emissions are assumed to have a social cost of carbon (SCC) of $100 per metric ton throughout. To analyze policy uncertainty, we model BAU and Pigouvian cases. For the BAU cases, the operating costs are as in Table 1. For the Pigouvian cases, we assume first-best carbon pricing so operating costs are incremented by the SCC times the emissions rate. Because carbon taxes and natural gas prices both increase the operating cost of generation

[23]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 O.A.3 for details.

from gas, our carbon tax simulations can be reinterpreted as sensitivity of our results to the price of natural gas.[24]

We do not consider coal technologies. Even ignoring environmental costs, coal technologies are dominated by our combined cycle gas technology at all levels of utilization. In fact, the long run average cost of coal is double that for combined cycle gas. Online Appendix O.A.2 details how costs would have to change to make coal viable in our model.

Finally, battery storage costs are shown in Table 1. Battery storage has no operating cost (no conversion losses) and can store electricity indefinitely. Note that the capital cost depends on the storage capacity of the battery which is measured in MWh.

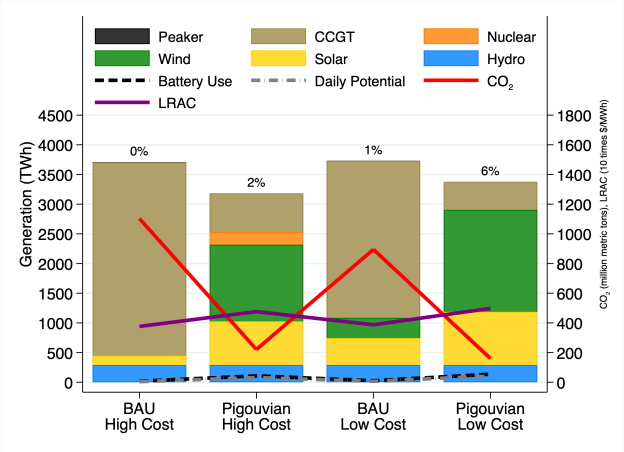
3.3 Solution algorithm

Because the demand curves are linear, the benefit functions $U_t(Q_t)$ are quadratic. Thus the planner's problem in (1) is a quadratic program with constraints, and we solve it directly using a publicly available algorithm described in Stellato et al. (2020).[25] This quadratic programming algorithm allows the objective function to be positive semidefinite, a feature that is necessary for our problem.

4 Electrification Results

The effects of electrification depend on the underlying demand and supply parameters, innovation, and public policy. Modeling the thirteen EIA regions illustrates the effects of renewable availability and its correlation with electricity demand. To capture the effects of innovation and/or subsidies for renewable generation, we analyze renewable capital costs that are either *High Cost*, i.e., given by Table 1, or *Low Cost*, i.e., are 25% lower than in Table 1. To capture the effects of different carbon policy environments, we analyze *business as usual (BAU)* cases with no carbon tax and *Pigouvian* cases with a carbon tax equal to the social cost of carbon of $100. This results in a two-by-two classification structure allowing for differing carbon policy and capital costs of renewables.

[24] A $10 increase in the carbon tax corresponds to a $0.53 per MMBTU increase in natural gas prices.
[25] The algorithm can be downloaded from `https://osqp.org/`.



g_baseline

Figure 3: Model Results: No Electrification

Notes: High Cost cases have renewable capital costs from Table 1 and Low Cost cases are 25% lower. BAU cases have carbon tax equal to zero and Pigouvian cases have carbon tax equal to the social cost of carbon ($100). Percentages above the rectangles show the share of potential renewable generation that is curtailed.

Before analyzing electrification, we first present the long-run equilibrium for the four cases without electrification. Figure 3 summarizes annual generation, carbon emissions, long run average cost of electricity generation, and battery statistics. In BAU High Cost, the vast majority of the generation comes from combined cycle natural gas, and CO_2 emissions are 1,104 million metric tons (mmt) per year, which is 30% lower than actual 2019 CO_2 emissions.[26] This difference arises because there is no modeled coal generation and because modeled electricity consumption is slightly lower than actual.[27] Imposing the first-best carbon tax (Pigouvian High Cost) reduces emissions dramatically to 221 mmt, and results in more diversity in generation technology including a small amount of nuclear and large amounts of wind and solar. The other cases in Figure 3 show the effect of a 25% reduction in capital costs of renewable generation with and without a carbon tax. The cheaper renewables result in higher levels of renewable generation and lower carbon emissions (895 mmt without the carbon tax and 160 mmt with the carbon tax). Comparing the Pigouvian cases, we see that cheaper renewables drive out nuclear generation. Result 4 shows this could potentially increase emissions, however, here we find that emissions decrease. Similarly, Result 6 shows

[26] Actual 2019 CO_2 emissions were 1604 mmt (Holland et al. (2022)). We use metric tons (mt) throughout.

[27] 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.

that a carbon tax could increase electricity consumption, but here electricity consumption (generation) is lower in the Pigouvian cases than in the BAU cases.[28]

Battery statistics shown in Figure 3 are Battery use and Daily Potential. Battery Use is the sum of charges added to the battery in TWh. Daily Potential is a measure of battery capacity, defined as $365K_s$ in TWh. It represents hypothetical battery use if the battery capacity were fully charged and discharged once a day. By either measure battery storage plays a small role. Batteries are most important in Pigouvian Low Cost. However, even in this case they account for a relatively small share of electricity generation. Moreover, Battery Use approximately equals Daily Potential which indicates that batteries are used approximately once per day and are not used for longer term storage. Because batteries are costly to build, they must be used frequently to cover capital costs. In particular, our results show it is cheaper to curtail up to 6% of renewable generation than to build battery capacity to store the available electricity. Generation from peaker gas plants occurs in the BAU cases, but it only accounts for about 3 TWh of generation, so it is not visible in Figure 3.

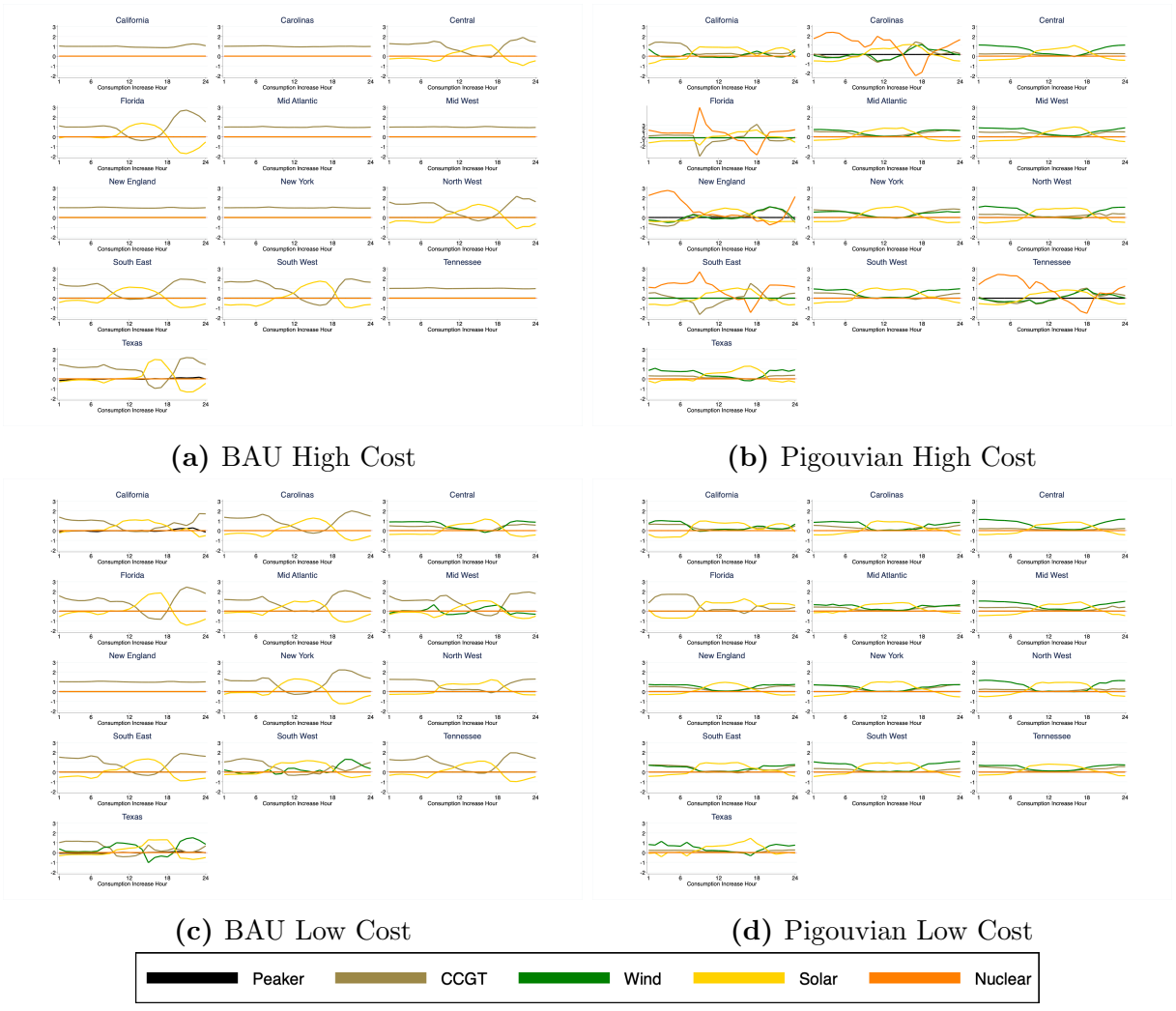
Long-run electrification may increase prices in some hours and induce capacity expansion. The additional capacity may directly affect emissions and can potentially lower prices and increase electricity consumption in other hours. To analyze these complex interactions, we first model small-scale electrification with exogenous usage profiles and then model large scale electric vehicle (EV) adoption with endogenous charge timing.

4.1 Small-scale electrification

To illustrate the effects of electrification, we begin with a simple scenario in which there is an increase in electricity consumption in a single hour of each day. In particular, for a given hour of the day h, the electrification is equal to one percent of observed average hourly consumption in that region, i.e., if $\bar{Q}$ is average consumption, then $\Delta\bar{E}_t = 0.01\bar{Q}$ for every t such that t modulo 24 is h.

Before presenting the LRECs, we illustrate the mechanisms of the model with *changes in generation shares* which we define as $\Delta s_i \equiv \sum_t \Delta q_{it} / \sum_t \Delta\bar{E}_t$ for technology i. These changes in generation shares from electrification are shown in Figure 4 for all consumption increase

[28] Result 6 does occur using iso-elastic demand curves rather than linear.



(a) BAU High Cost **(b)** Pigouvian High Cost

(c) BAU Low Cost **(d)** Pigouvian Low Cost

Figure 4: Changes in generation shares from electrification by hour

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

hours h. In BAU High Cost, Figure 4 (a), there are seven regions in which electrification in any hour of the day simply leads to a 1:1 increase in generation from combined cycle natural gas.[29] The other six regions show an interplay between natural gas and solar generation. Electrification in the evening leads to a more than 1:1 increase in natural gas combined cycle generation which is offset by a reduction in solar generation. This may seem counterintuitive at first, because electrification in, say, hour 24 obviously does not directly affect generation from solar in that hour. But it does increase the entry of combined cycle natural gas, and

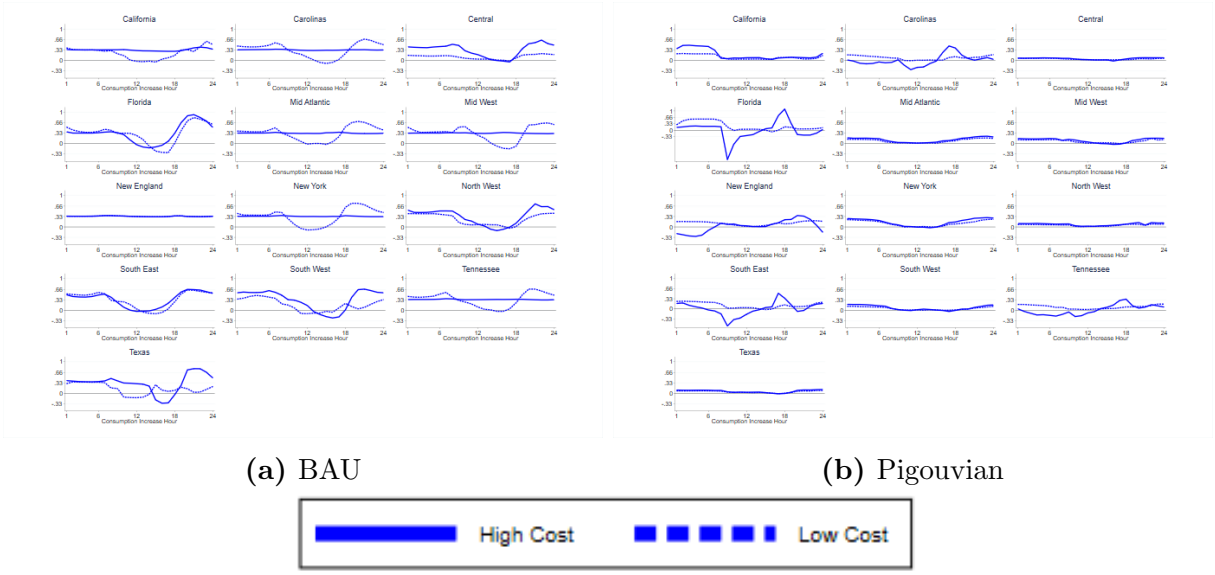
[29]The seven regions are Carolinas, MidAtlantic, MidWest, New England, New York, Tennessee, and California.

that extra capacity can generate electricity in other hours, which displaces solar in those hours. In this case, the sum of the effects over all hours due to electrification in hour 24 yields an increase in natural gas generation and a decrease in solar generation. For other hours of the day, the effects vary from a mixed response by solar and natural gas; to a 1:1 response from solar; to a more than 1:1 response from solar which is offset by a reduction in natural gas generation. As we will see, these responses may result in dramatically different effects on emissions.

Figures 4 (b)-(d) show an even richer set of responses to electrification. In Pigouvian High Cost, a significant share of generation is nuclear in regions with limited renewable availability, and Figure 4 (b) shows nuclear generation responds to electrification. For example, in Florida, electrification in hour 18 results in a more than 1:1 increase in solar and natural gas generation, which is offset by a decrease in nuclear generation. Conversely, electrification in hour 9 results in a more than 1:1 increase in nuclear generation offset by a reduction primarily in natural gas. Four other regions also show quite large responses by nuclear generation. In regions with good renewable availability (e.g., Central) electrification results in approximately a 1:1 response from solar during the day and wind during the night.

With cheaper renewables, Figures 4 (c) & (d) show that electrification during the afternoon results in a 1:1 or more increase in solar generation in all regions except New England. Responses to electrification in other hours may involve changes to solar, wind, and natural gas. In Figure 4 (d), for every region except Florida electrification during the day results in about a 1:1 increase in solar while electrification at night results in about a 1:1 increase in wind with solar offset if the wind increase is more than 1:1. However in some regions, natural gas is also responding, e.g., New York. Without carbon pricing, Figure 4 (c), much more of the response is from natural gas. In fact, in all regions except Central electrification at night results in a 1:1 or more than 1:1 response from natural gas with offsetting reductions in solar generation.

Figure 5 aggregates the changes in generation shares to give the LRECs due to electrification in hour h as defined in (9). For BAU High Cost, in seven regions natural gas responds 1:1, so the LREC is equal to 0.34 mt per MWh for each hour which is the emissions rate of combined cycle natural gas (Figure 5 (a) solid line). In the other six regions, the LRECs



(a) BAU **(b)** Pigouvian

fig_LRME

Figure 5: LRECs from electrification by hour

Notes: Vertical axis is the LREC (mt/MWh) across all hours from a one percent shock to demand in only hour h each day of the year.

can be greater or less than 0.34 and can even be negative. For example, in Florida in the evening, the LREC exceeds 0.34 due to the more than 1:1 increase in natural gas generation offset by a decline in solar. In fact, the LREC during these hours illustrates Result 2 because it exceeds the highest emissions rate of any technology (0.52 for peaker gas).[30] Conversely, during the afternoon solar generation may respond so that the LREC is less than 0.34, and may even be negative if solar responds more than 1:1. The negative LREC is consistent with Result 1.

With lower cost renewables in BAU, Figure 5 (a) dashed line, the LREC during the afternoon is more likely to be below 0.34, e.g., in Carolinas. Thus, cheaper renewables can decrease LRECs. However, in the evenings, the cheaper renewables actually *increase* the LRECs in some regions, e.g., Carolinas. This is consistent with Result 4 showing that the LRECs can be higher with lower cost renewables.

Figure 5 (b) shows the LRECs from electrification under a Pigouvian carbon tax. In general, the LRECs are lower and are close to zero across all hours in some regions, e.g., Central, MidAtlantic, MidWest, Northwest, and Texas. However, in some regions for some hours, the LRECs may exceed 0.34, e.g., California in the early morning, or can be negative.

[30] Over all the possibilities in Figure 5, 0.52 is exceeded by 7% of the cases.

Consistent with Result 6, LRECs can be higher with the carbon tax, e.g., California in the early morning for BAU, but the Pigouvian carbon tax generally lowers the LRECs. When electrification affects nuclear power, e.g., Florida, the LRECs can be large and positive or large and negative. This implies that the emissions from electrification may be highly sensitive to the timing of electrification.

The results in Figure 5 illustrate the range of LRECs from electrification in a given hour and are the natural analog to short run marginal emissions. Unlike the short run, however, aggregating these effects across hours to capture the effects of a policy that uses electricity in more than one hour per day may not be reliable because additional generation capacity can be used in many hours.[31]

To analyze more complicated electrification scenarios, we consider electrification profiles which increase electricity use in more than just one hour. For example, green hydrogen production or other industrial processes may run essentially continuously, which we model with a Flat electrification profile in which each hour of the year has the same increase in consumption, i.e., $\Delta\bar{E}_t = 0.01\bar{Q}$ for every t. Similarly, we define six other electrification profiles: Daytime, Nighttime, Summer, Winter, Summer Day, Winter Night, to illustrate electrification at different times or seasons, for example, from lighting, air conditioning, or space heating.[32]

Figure 6 shows the LRECs for each of these electrification profiles for the thirteen regions. (The underlying data are given in Online Appendix Tables O.A.2 to O.A.8.) Two reference levels are zero and 0.34 mt per MWh, which is the emissions rate of combined cycle natural gas. Four points are worthy of note. First, there is substantial heterogeneity in the LRECs: ranging from above 0.6 to less than -0.2. The heterogeneity narrows with carbon pricing and cheaper renewables but remains substantial. Both carbon pricing and cheaper renewables lead to increases in the variation of marginal costs, and faced with competition and entry in the long run, the higher cost and higher emission plants (i.e., lower productivity plants) are driven from the market.[33] Second, LRECs tend to be lower in Daytime (compared to

[31] If prices don't change, taking a linear combination of the individual hourly LRECs is equal to the LREC for a more complicated use profile, but this will not work in general. Similarly, a small increase in electrification does not necessarily have the same LREC as a large increase.

[32] For example, for Daytime we use $\Delta\bar{E}_t = 0.01\bar{Q}$ for every t such that t modulo 24 is in $\{8, ..., 18\}$.

[33] This is similar to Syverson (2004).

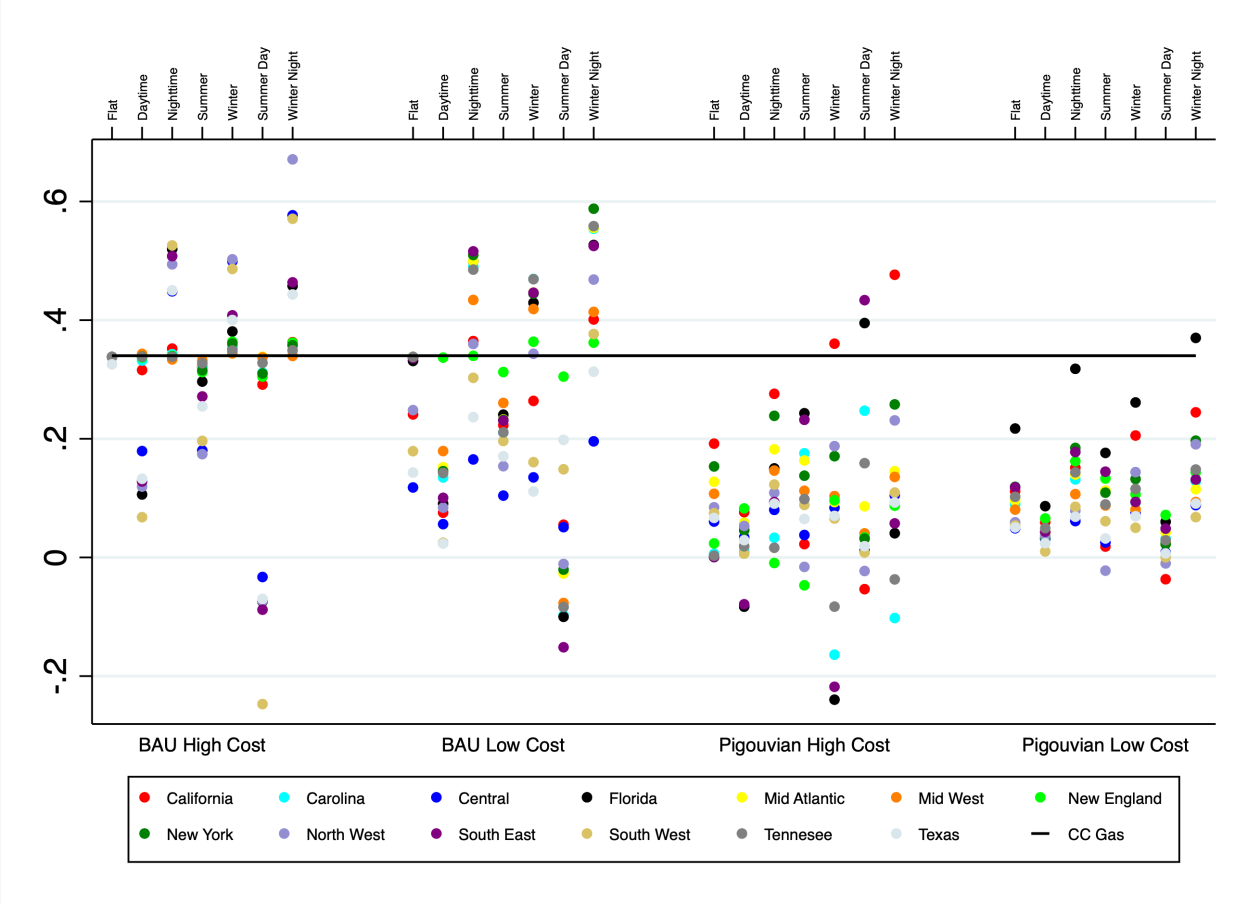


Figure 6: LRECs for various electrification profiles

Notes: Vertical axis is the LREC (mt/MWh) across all hours for a change in demand (equal to one percent of observed consumption in a region) during hours specified by the use profile. "Flat": the change in demand occurs in all hours. "Daytime": the change occurs from 8am to 6pm. "Nighttime": the change occurs from 7pm to 7am. "Summer": the change occurs from May to October. "Winter": the change from November to April. "Summer Day": the change occurs from May to October from 8pm to 6pm. "Winter Night": the change occurs from November to April from 7pm to 7am.

Nighttime), Summer (compared to Winter), and Summer Day (compared to Winter Night). This effect holds because these are the times when solar generation responds more to electrification. This pattern indicates that the LRECs for air conditioning, for example, are less than for space heating. However, this pattern does not hold with Pigouvian High Cost, likely because nuclear is responding in this scenario. Third, LRECs are generally lower with carbon taxes, but are not substantially lower with cheaper renewables. This perhaps arises because cheaper renewables do not necessarily reduce emissions of electrification, so their effects may be smaller when aggregated across an electrification profile. Finally, negative

LRECs are possible, particularly with the summer profile, but occur in only a minority of regions.

4.2 EV adoption

Large-scale electrification, such as EV adoption, requires substantial increases in electricity usage across multiple hours. We analyze the effects of replacing the entire light duty vehicle fleet with electric vehicles by first assuming electricity use of 0.25 kWh per mile at 68 degrees Fahrenheit and adjusting for locational differences in temperature. This gives a county-level electricity usage per mile, which we then multiply by the county-level vehicle miles traveled (VMT) and aggregate up to the EIA region to obtain annual EV electricity demand for each region.[34]

The EV owner may have flexibility over the hours they use electricity to charge the EV's battery. This flexibility may have different implications for emissions and may be influenced by a mixture of consumer preferences, market behavior, and public policy that determine where charging stations are located (e.g., in apartment complexes or shopping malls). We define five charging profiles which determine the charging hours. The EPRI profile charges mostly at night (see Figure O.A.11) and is largely consistent with recent work that estimates actual charging behavior in California (Burlig et al. (2021)). The Flat profile distributes charging evenly across all hours. In the Carbon Min profile, charging is optimally distributed across hours such that the total emissions of carbon are minimized. Two other optimized profiles, the Charge Cost Min and Welfare Max profiles, minimize the cost of charging the vehicles and maximize welfare as defined in Section 2. To determine the three optimized profiles, we use an inner and outer optimization procedure. Given a candidate profile, the inner optimization solves the planner's problem (1) as described above to determine the long-run equilibrium when vehicles are charged according to the candidate profile. The outer optimization then searches over the space of feasible profiles to find the profile that optimizes the appropriate objective (carbon emissions, welfare, or charging costs).[35]

[34] We use miles traveled from the US EPA Moves model for year 2011 light duty vehicles (obtained from Holland et al. (2016)).

[35] A feasible profile is an element in the 24-dimensional unit simplex with an additional restriction that the maximum value for any hour is 0.4. The precision of this procedure is described in Online Appendix O.A.4.

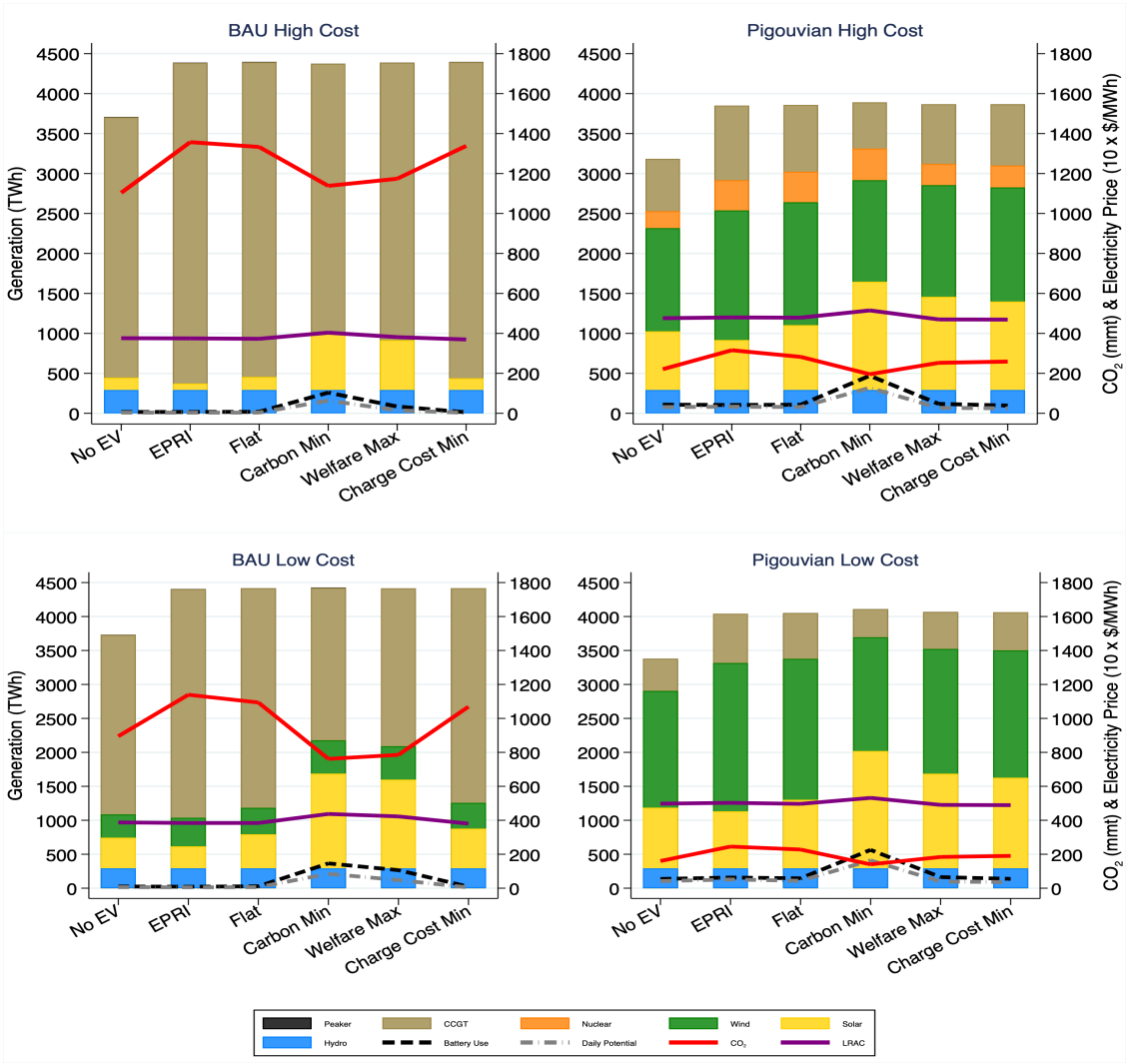


Figure 7: Effects of 100% EV adoption for Different Charging Profiles

Notes: The "Flat" charging profile has equal charging in all hours; the "EPRI" profile assume most charging at night; the "Carbon Min" profile minimizes carbon emissions; the "Charge Cost Min" profile minimizes the cost of EV charging; the "Welfare Max" profile maximizes welfare.

Figure 7 summarizes the generation, emissions, and battery statistics for the baseline without EVs (No Ev) as well as for 100% EV adoption under the various charging profiles.[36] Consider first the BAU High Cost case. Under the EPRI charging profile, using EVs for 100% of light-duty VMT *reduces* long-run renewable generation, which is consistent with Result 2, and increases carbon emissions from electricity by 255 mmt annually. However, the current light-duty gasoline-powered vehicle fleet emits approximately 1040 mmt of carbon emissions annually and these emissions are completely eliminated under 100% EV adoption.

[36] As before, there is a small amount of peaker gas generation in the BAU cases that is not visible in the figure.

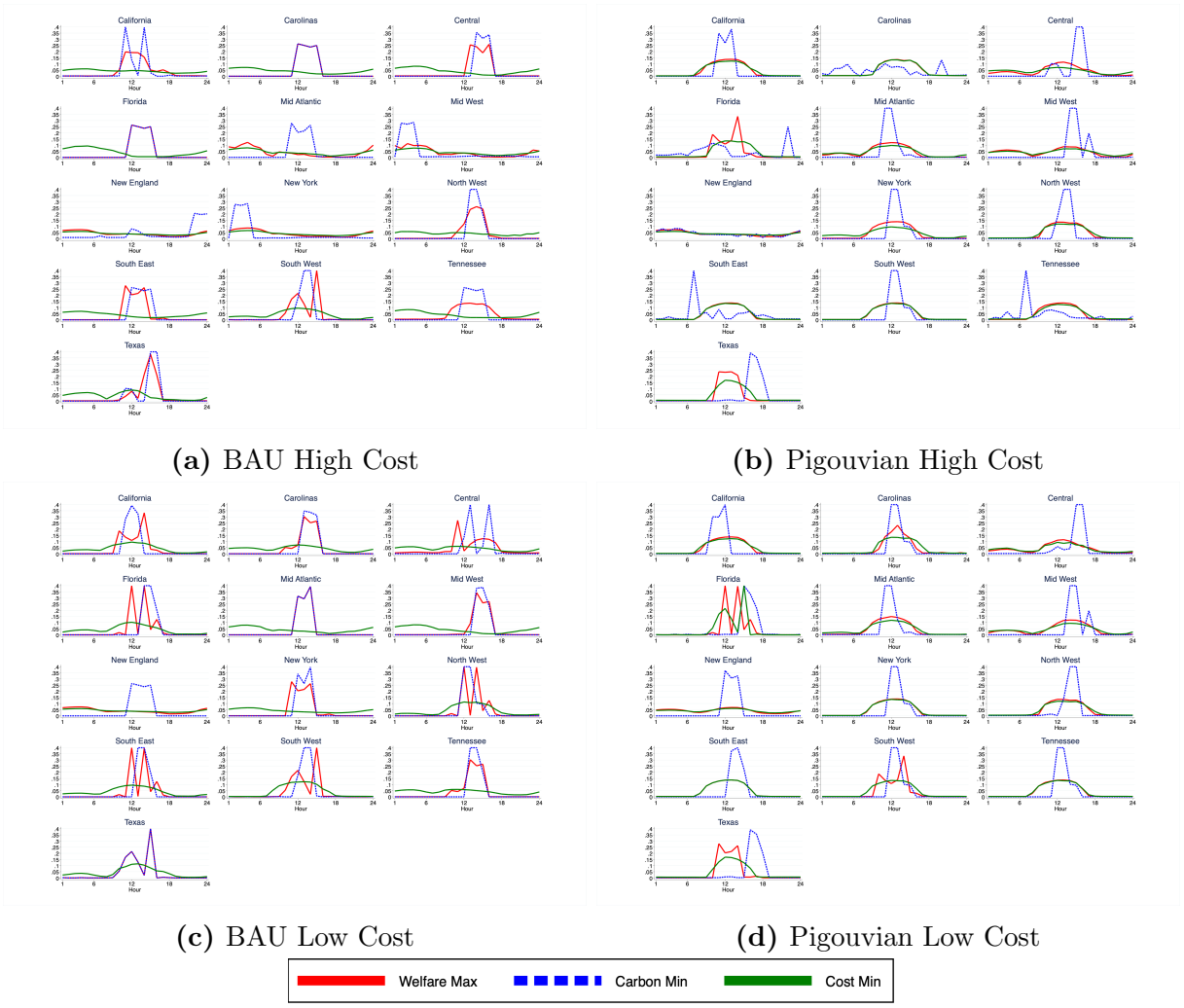
So in this case EV adoption substantially reduces carbon emissions from transportation. The results are similar for the Flat and Charge Cost Min profiles. However with the Carbon Min profile, EV adoption only increases electricity sector emissions by 35 mmt because it increases long-run renewable generation. This results in even larger emissions reductions from transportation. The Carbon Min profile also leads to a large increase in battery storage. This charging profile concentrates charging in a few hours, which greatly increases prices during those hours and increases arbitrage opportunities for the batteries. In this case, Battery Use exceeds Daily Potential indicating that the battery storage is charged and discharged more than once per day on average. The Welfare Max profile, which considers all benefits and costs, does not induce as much solar generation, has slightly higher carbon emissions, and lower battery storage.

These patterns generally hold in the other cases in Figure 7. Importantly, EV adoption substantially reduces carbon emissions from transportation and can increase or decrease renewables depending on the charging profile. One important difference, however, is that electricity-sector emissions *decrease* when moving from no EVs to 100% EV adoption under the Carbon Min profile. For example, in the BAU Low Cost case, the Carbon Min profile leads to emissions that are 132 mmt lower than without EVs. This striking result shows that it is possible to completely electrify vehicle transportation while also reducing electricity-sector carbon emissions.[37] However, this is not efficient and emissions increase slightly for Welfare Max in most cases.

The comparisons across the profiles suggest a tension between the environmental effects and the cost and convenience of charging. Figure 8 shows the optimized charging profiles for each region.[38] In the BAU High Cost, the Cost Min profile spreads charging across many

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

[38] The optimized charging profiles in Figure 8 should be interpreted carefully for several reasons. First, "spikes" in the charging profile may indicate indifference between charging in two neighboring hours. For example, with the Pigouvian cases, the Welfare Max charge profile reflects a perfectly competitive market, i.e., optimization by a price taking EV owner. If the electricity prices are equal in two hours, the EV owner is indifferent between charging in the two hours. In other words, there may not be a unique optimizing profile. Second, the Cost Min profile captures the behavior of a monopsony EV owner rather than a price taker. Because the supply curve is very elastic the monopsony distortion is likely small. Third, for the Carbon Min profile the "spikes" tend to represent unique optimizers which concentrate charging in limited hours to "spike" the electricity price and induce renewable entry.



(a) BAU High Cost

(b) Pigouvian High Cost

(c) BAU Low Cost

(d) Pigouvian Low Cost

Figure 8: Optimal EV charging profiles for each region

Notes: Vertical axis is the percent of time charging occurs in the given hour. "Welfare Max" maximizes welfare; "Carbon Min" minimizes carbon emissions; "Cost Min" minimizes the cost of charging EVs.

hours or charges primarily at night. This is similar to the EPRI or Flat profiles but contrasts with the Carbon Min and Welfare Max profiles. The Carbon Min profiles generally charge in the midday hours. Charging at these times increases solar capacity which provides emissions free generation both in the hours during which the cars are charged as well as other hours when the sun is shining. For example, in Tennessee, the Cost Min profile charges primarily at night, but the Carbon Min and Welfare Max profiles charge primarily during the day with the Carbon Min profile charging primarily in a few hours. This difference across profiles still holds with cheaper renewables (BAU Low Cost), but in the Pigouvian cases the difference is reduced. In fact, for the Pigouvian Low Cost case, the Cost Min and Welfare Max

charging profiles align almost exactly for most regions, although the Carbon Min profile still concentrates charging in fewer hours. Thus carbon pricing aligns the private incentives (Cost Min) with the social incentive (Welfare Max) for most regions.[39]

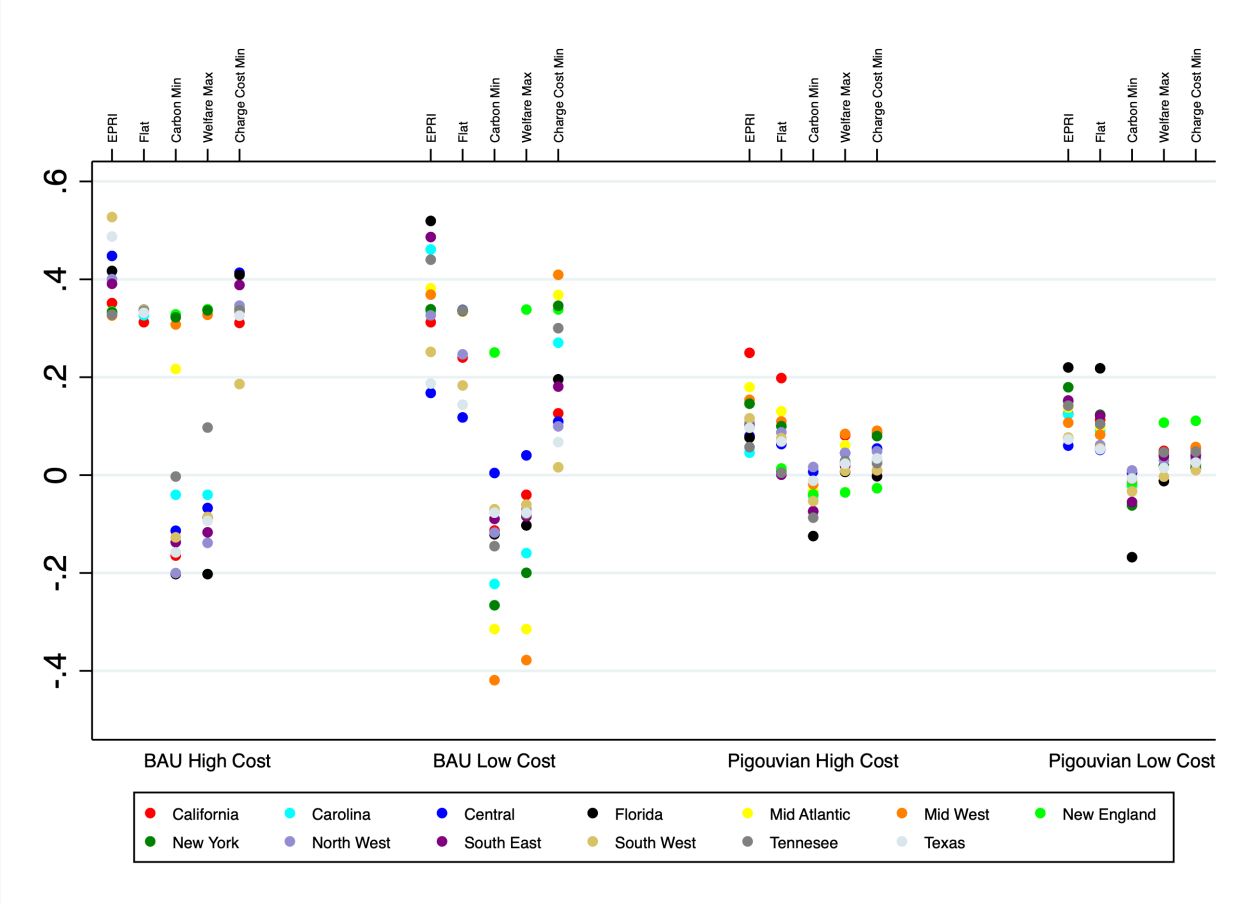


Figure 9: LRECs for various EV Charging Profiles

Notes: Vertical axis is the LREC (mt/MWh) across all hours for a change in demand from the various profiles. The "Flat" profile has equal charging in all hours; the "EPRI" profile assume most charging at night; the "Carbon Min" profile minimizes carbon emissions; the "Welfare Max' profile maximizes welfare; the "Charge Cost Min" profile minimizes the cost of EV charging.

The emissions effects of EV adoption can be summarized by LRECs. Figure 9 shows the LRECs disaggregated across regions and charging profiles. (The underlying data are given in Online Appendix Tables O.A.9 to O.A.13.) For BAU High Cost, the LREC for the Flat profile is approximately 0.34 mt per MWh for all regions, which is the emissions rate of combined cycle natural gas. The EPRI profile has higher LRECs across most regions. The

[39]Intuitively, with Pigouvian pricing, the shadow cost of charging in a given hour is the electricity price so welfare is maximized by charging in low price hours. Similarly, charging costs are minimized by charging during low price hours.

Carbon Min and Welfare Max profiles have much lower LRECs, including negative LRECs across most (but not all) regions. In contrast the Charge Cost Min profile has positive LRECs like the EPRI or Flat profiles.

With cheaper renewables (BAU Low Cost), the LRECs vary substantially across regions and across charging profiles. For example, the EPRI profile in Florida results in an LREC of 0.5, whereas the Carbon Min profile in the Mid West results in an LREC of -0.4. Here the Carbon Min and Welfare Max profiles both have large negative LRECs for almost all regions. Again, the Charge Cost Min profile has positive LRECs like the EPRI or Flat profiles.

With carbon pricing, the differences across regions and across charging profiles are much smaller. In particular, the LRECs are below 0.34 for all regions and are close to zero or are negative for the three optimized profiles. Importantly, the difference between Welfare Max and Charge Cost Min are much smaller, illustrating the alignment of these two objectives under Pigouvian carbon pricing. Note that the Charge Cost Min captures the costs of charging the vehicles to EV owners under our maintained assumption that consumers face the time-varying prices. If EV owners do not face the time-varying wholesale prices, charging may be more accurately captured by the EPRI or Flat profiles, both of which have higher LRECs than socially optimal.

5 Conclusion

Electrification of energy use combined with decarbonization of the electricity sector is a promising path for addressing climate change. However, changes in electricity demand may help or hinder decarbonization due to feedback effects from electrification on investment in renewables and fossil power. We construct a model that captures crucial aspects of the electricity industry such as time-varying demand, renewable intermittency, costly storage, and endogenous generation capacity while abstracting away from legacy investments and transition costs. This framework provides a transparent and tractable tool for analysis and policy assessment.

Our theoretical model demonstrates that several surprising long-run effects are possible from electrification. Most surprisingly, we show that electricity demand growth (for example,

due to greater EV penetration) could potentially decrease total emissions in the electricity sector by crowding in renewable investment and crowding out fossil investment. Using simulations from our calibrated model, we show that negative long-run emission changes are possible if EV charging is done in a way that minimizes emissions. Depending on the region, this generally involves EV charging in the daytime, and construction of charging stations in shopping centers and workplaces could facilitate daytime charging. However, current charging patterns are mostly in the evening, which can lead to greater use of fossil fuels and a crowding out of renewables in the long run. Overall, the effect of EV charging on emissions exhibits considerable heterogeneity across regions, policy, and cost assumptions. Pigouvian taxation and lower cost renewables tend to reduce this heterogenity and make negative long-run emission changes less likely. This illustrates the complicated long run interactions between electrification and other policies such as a carbon taxes and renewable subsidies.

Negative emissions are a tantalizing prospect, however EV charging to achieve negative emissions may not be optimal when considering the overall welfare gains from EV adoption. To calculate these gains, one would need to supplement the welfare measure in this paper with additional consideration of the consumer surplus gains or losses from EVs and consumer preferences for charging times along with a detailed analysis of welfare from avoided light-duty vehicles (e.g., consumer surplus from gasoline vehicles, operating costs, capital costs, and externalities from driving gasoline vehicles).

Although it is known that the environmental effects of EV adoption depend on the timing of charging (Holland et al. (2022)), our results 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. Cases in which the LREC differ significantly from their short run counterparts create an interesting dilemma for those who want to reduce the carbon footprint of their electricity consumption. Choosing to consume electricity in hours with low short run marginal emissions may be counterproductive in the long run. Accounting

for both the short run and long 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 uncertain. We assume no market power in the long run although electricity market participants may have some pricing power in the short run. Similarly, we do not model learning by doing, scale economies, or additional market failures such as learning spillovers and information asymmetries. Additionally, legacy technologies and transition costs may play a role in the feasibility of grid investments. More detailed demand calibrations and modeling of transmission congestion are important possible extensions of our work. Finally, actual solar and wind generation data for several missing regions would allow better capacity factor estimates. Given these caveats, our theoretical and calibration results provide important insights into electrification in the long run.

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Appendix: Proofs

Proof of Lemma 1: Suppose $q_{i't} < f_{i't}K_{i'}$. The FOC for $\lambda_{i't}$ implies that $\lambda_{i't} = 0$ so (4) then implies that $p_t \leq c_{i'}$. But $q_{it} > 0$ implies from (4) that $p_t = c_i + \lambda_{it} \geq c_i$, which contradicts the assumption $c_i > c_{i'}$. ■

Proof of Lemma 2 : For notational simplicity, assume the technologies have unique costs. Because Lemma 1 implies a unique ordering of the technologies, let $\rho_{it} \equiv U'(\sum_{i' \leq i} f_{i't}K_{i'} - b_t - \bar{E}_t)$ be the marginal benefit if all technologies with operating cost less than or equal to c_i generate at capacity and if net battery charging is b_t. Falling marginal benefit implies that $\rho_{it} > \rho_{(i+1)t}$ for all i. Moreover, it is easy to show that technology i operates at capacity in period t if $\rho_{it} > c_i$.

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

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 $\min_i\{\max\{c_i, \rho_{it}\}\} = \min\{\rho_{1t}, \rho_{2t}, ..., \rho_{(\iota-1)t}, p_t, c_{(\iota+1)}, c_{(\iota+2)}, ..., c_I\} = p_t$.■

Proof of Lemma 3: First note that $\phi_t = p_t$ from (5) . If $S_t = 0$, then $\mu_t = 0$ by the FOC for μ_t, so (6) implies that $p_{t+1} - p_t = \phi_{t+1} - \phi_t \leq 0$. If $0 < S_t < K_s$, then $\mu_t = 0$ and the inequality in (6) binds so $p_{t+1} - p_t = 0$. If $S_t = K_s$, then $\mu_t \geq 0$ and $0 = p_{t+1} - p_t - \mu_t \leq p_{t+1} - p_t$, so $p_{t+1} \geq p_t$. ■

Proof of Lemma 4 : From (4), we have that $p_t - c_i \leq \lambda_{it}$. Because $\lambda_{it} \geq 0$ we have $\lambda_{it} \geq \max\{p_t - c_i, 0\}$. Proof by contradiction[40] shows that $\lambda_{it} = \max\{p_t - c_i, 0\}$. Substitution

[40]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.

in (7) and multiplying by K_i implies that

$$0 = \sum_t \max\{p_t - c_i, 0\} f_{it} K_i - r_i K_i$$

$$= \sum_t (p_t - c_i) q_{it} - r_i K_i.$$

where the last equality 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 $p_t = c_i$.[41]

For the battery, to derive the condition from (8) we must evaluate $\sum_t \mu_t$. Lemma 3 allows us to identify a charging cycle, C: the time period over which the price falls while the battery is empty, then the price is flat while the battery charges, then the price increases while the battery is full, and finally the price is flat while the battery discharges completely. For this charging cycle C, let $\underline{p}$ be the lower price while the battery is charging, and let $\bar{p}$ be the higher price while the battery discharges. To evaluate $\sum_{t\in C} \mu_t$, first note that $\mu_t = 0$ if $S_t < K_s$ and $\mu_t = p_{t+1} - p_t$ if $S_t = K_s$. In the charging cycle, $\mu_t = 0$ except when the price is rising. During this time, the sequence of μ_t will be $p_{t_1} - \underline{p}$, $p_{t_2} - p_{t_1}$, $p_{t_3} - p_{t_2}$, ..., $\bar{p} - p_{t_n}$, which implies that $\sum_{t\in C} \mu_t = \bar{p} - \underline{p}$. To evaluate $\sum_{t\in C} -p_t b_t$ over the cycle C, 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 $\sum -p_t b_t = -\underline{p} K_s$. 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 $\sum -p_t b_t = \bar{p} K_s$. Thus for the charging cycle C, $\sum_{t\in C} -p_t b_t = (\bar{p} - \underline{p}) K_s$. But this implies $\sum_{t\in C} -p_t b_t = K_s \sum_{t\in C} \mu_t$. Summing over all charging cycles and using (8) establishes that $\sum_t -p_t b_t = r_s K_s$. ■

Proof of Result 1: Consider a two period model with two technologies. Let h and l indicate the high and low demand periods, and $D_h(p) \geq D_l(p)$ for each p. Technology 1 (renewable) has $c_1 = \beta_1 = 0$, and technology 2 has $c_2 > 0$ and $\beta_2 > 0$. All capacity factors equal one. Assume that $r_1 < r_2 + 2c_2$. This ensures that $p_l < c_2$ so $q_{2l} = 0$. The equilibrium then has capacities given by $K_1 = D_l(p_l)$ and $K_1 + K_2 = D_h(p_h)$, and prices (from Lemma 4) given by $p_l + p_h = r_1$ and $p_h = c_2 + r_2$. Note that p_l and p_h are determined by r_i and c_i so they are not affected by increments to demand. Emissions are only in period h and equal $\beta_2 K_2$.

[41] 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 $\max\{p_t - c_i, 0\} f_{it} = (p_t - c_i) f_{it} = (p_t - c_i) q_{it}/K_i$.

Now consider an increment $\Delta\bar{E}_h > 0$ to demand in period h. Since prices are unaffected, K_1 is also unaffected, so $\Delta K_2 = \Delta\bar{E}_h > 0$. But this implies that emissions increase, i.e., $\beta_2 \Delta K_2 > 0$.

However, consider a demand increment $\Delta\bar{E}_l > 0$ in period l. Since p_l is unaffected, $\Delta K_1 = \Delta\bar{E}_l$. But because p_h is also unaffected, we have $\Delta K_2 = -\Delta\bar{E}_l < 0$, which implies that emissions decrease, i.e., $\beta_2 \Delta K_2 < 0$. Thus the LREC is negative in this case. ■

Proof of Result 2: Consider the same model as in the proof of Result 1 except assume $f_{1l} = 0$ (Technology 1 is intermittent) and assume that $c_2 + r_2 > r_1 > c_2$. This ensures that p_h and p_l are both greater than c_2. The equilibrium has capacities given by $D_l(p_l) = K_2$ and $D_h(p_h) = K_1 + K_2$, and equilibrium prices (from Lemma 4) are $p_h = r_1$ and $p_l + p_h = 2c_2 + r_2$. Note again that prices are not affected by increments to demand.

Now consider a demand increment $\Delta\bar{E}_l > 0$ in period l. To keep p_l constant, we have $\Delta K_2 = \Delta\bar{E}_l$. But because $K_1 + K_2$ must stay constant to keep p_h constant, we have $\Delta K_1 = -\Delta K_2 < 0$ and renewable capacity, K_1, decreases. Emissions in each period increase by $\beta_2 \Delta K_2$. The LREC is given by

$$\frac{\beta_2 \Delta K_2 + \beta_2 \Delta K_2}{\Delta\bar{E}_l} = 2\beta_2.$$

■.

Proof of Result 3: Consider a two period model with a single dispatchable technology and $c_1 = 0$ but $r_1 > 0$. Assume the demand curves are linear with common slope s. Suppose that, in the initial equilibrium, we have $D_l(p_l) = K_1$ and $D_h(p_h) = K_1$ and prices (from Lemma 4) satisfy $p_l + p_h = r_1$. Consumer surplus to existing consumers is $CS_i = U_i(K_1) - p_i K_1$ for $i \in \{l, h\}$.

Now consider a demand increment $\Delta\bar{E}_h > 0$ in period h. It is easy to see that $0 < \Delta K_1 < \Delta\bar{E}_h$ and that $\Delta p_h = -\Delta p_l \equiv \Delta p > 0$ where Δp is determined such that $K_1 + s\Delta p = K_1 - s\Delta p + \Delta\bar{E}_h$. Now consider $\Delta CS_l + \Delta CS_h$. Begin with period l. In period l the price falls, so the consumer surplus gain is the trapezoid with height Δp and bases K_1 and $K_1 + s\Delta p$. So $\Delta CS_l = K_1 \Delta p + 0.5s(\Delta p)^2$. In period h the price rises, so the consumer surplus loss is

the trapezoid with height Δp and bases K_1 and $K_1 - s\Delta p$. So $-\Delta CS_h = K_1\Delta p - 0.5s(\Delta p)^2$. Thus $\Delta CS_l + \Delta CS_h = s(\Delta p)^2 > 0$. ■

Proof of Result 4 : 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. Consider a model with two time periods, h and l, and three technologies. Technology 1 (intermittent renewable) is available only in period l, *i.e.,* has capacity factors $f_{1l} = 1$ and $f_{1h} = 0$, and Technology 2 (nuclear) and Technology 3 (fossil) are dispatchable with $0 = c_1 < c_2 < c_3$ and $0 = \beta_1 = \beta_2 < \beta_3$. With two periods, only two technologies can have positive capacities.

With high cost renewables, i.e., high r_1, generation is only from nuclear and fossil and equilibrium prices are $p_h + p_l = 2c_2 + r_2$ and $p_h = c_3 + r_3$, with $r_1 > p_l$ so renewables do not enter. In this case, carbon emissions are $\beta_3(D_h(p_h) - K_2)$. If renewable capital costs are lower, such that $r_1 < p_l$, then renewables enter until $r_1 = p_l' < p_l$. Because $p_h = c_3 + r_3$, it is unchanged. But then there is no nuclear capacity because $p_h + p_l' < p_h + p_l = 2c_2 + r_2$. Because the renewable capacity is only available in period l, fossil capacity is higher and carbon emissions are $\beta_3 D_h(p_h)$ so the lower renewable costs have higher carbon emissions.

Now let there be a small increase in demand $\Delta\bar{E}$ in both periods. Consider first the high cost renewable case $r_1 > p_l$. Prices in the two periods must stay the same, so capacity must increase. In period l only nuclear is generating and so we have $\Delta K_2 = \Delta\bar{E}$. In period h both nuclear and fossil are generating so we have $\Delta K_2 + \Delta K_3 = \Delta\bar{E}$ which implies $\Delta K_3 = 0$. Thus emissions do not increase and so the LREC is equal to zero.

In the low cost renewable case, once again prices must stay the same so capacity must increase. In period l only renewables are generating so we have $\Delta K_1 = \Delta\bar{E}$. In period h only fossil is generating, so we have $\Delta K_3 = \Delta\bar{E}$. Thus emissions increase by $\beta_3\Delta K_3 > 0$ and so the LREC is positive. Thus the LREC is higher with low cost renewables. ■

Proof of Result 5: To show that renewable capacity can increase or decrease if r_s decreases, consider the exact same model as in the proof of Result 2. Assume at first that storage is expensive, such that $r_s > p_h - p_l$. Then storage is not profitable, and no storage is built. If storage is less expensive, then Lemma 4 implies storage enters until $r_s = p_h' - p_l'$. This drives down the high price and drives up the low price. Since $p_h' < p_h = r_1$, there is no renewable capacity, additional fossil capacity enters, and carbon emissions increase.

Proof of Result 6 : The first statement follows directly from the increase in costs of any polluting technology. Consider the exact same model as in the proof of Result 1 except now there is a carbon tax in place. It is easy to verify that both technologies are used in period h and the equilibrium prices are $p_l + p_h = r_1$ and $p_h = c_2 + \beta_2\tau + r_2$ if $p_l < c_2 + \beta_2\tau$. Now consider $\Delta\tau > 0$. Clearly $\Delta p_h = \beta_2\Delta\tau > 0$ and $\Delta p_l = -\Delta p_h < 0$ 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.

To prove the statement about the LREC, once again consider exact same model as in the proof of Result 1, but this time assume that there is no carbon tax. As shown in that proof, the LREC due to a demand increment in period l is negative. Next assume there is a carbon tax that is sufficiently large that it drives out technology 2. There is only technology 1 in the long run equilibrium, and this technology has no emissions, so that the LREC due to a demand increment in period l is zero. Hence the LREC with a carbon tax is greater than the LREC without the carbon tax. ■

For Online Publication: Appendix

O.A.1 Model extensions

ode-extend

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

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

The ramping constraint is fixed as a percentage of capacity. Generation can't increase by more than this amount from one hour to the next.

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

$$r_i + \eta_i K_i.$$

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

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

O.A.2 Consideration of generation from coal

pendix-coal

Using the same EIA data source as for the other technologies, the capital cost of new coal generation is \$374,608 per MW and the operating cost is \$22.48 per MWh. As discussed in the main text, coal is dominated by natural gas at our baseline cost values for all technologies.

To see the degree to which cost values have to change before coal becomes a viable generation technology, we consider a sensitivity analysis in which we increase the ratio of operating cost of gas generation to operating cost of coal generation or decrease the ratio of capital cost of coal generation to capital cost of gas generation. The results are shown in Figure O.A.10. Keeping the capital cost ratio at baseline, the operating cost ratio of gas to coal would have to increase to 2.85 (a factor of 2.4 from baseline of 1.19) before any coal generation is used at all in the long run equilibrium. Keeping the operating cost ratio at baseline, the capital cost ratio of coal to gas would have to decrease to 1.41 (a seventy percent decrease from baseline of 4.71) before any coal generation is used at all. In our baseline, the vast majority of generation is from natural gas. In the event that gas costs increase significantly from baseline and coal capital costs decrease significantly from baseline, much of this generation would switch from gas to coal.

O.A.3 Renewable capacity factors for missing regions

:RenCapFac

EIA Form 930 (USEIA 2019a) is missing hourly solar generation for New York and hourly wind generation for Carolinas, Florida, SouthEast, and Tennessee. We estimate the missing capacity factors as follows. For New York solar, we use the NREL National Solar Radiation Database (NSRDB, NREL (2021)) which provides half hour values for Direct Normal Irradiance (DNI) in watts per square meter. We use Boston (ISONE) and Philadelphia (PJM/MIDA) as comparisons to generate capacity factors for New York (NYISO). First we collapse the DNI data by hourly average and market. We then regress capacity factor on DNI for ISONE and PJM/MIDA for daylight hours. Using these regression results, we predict capacity factors for NYISO and bound these predictions between 0 and 1 (set to zero if DNI is zero).

For the wind capacity factors in Carolinas, Florida, SouthEast, and Tennessee, we collect data on wind speed from NREL for year 2014 (NREL (2014)) by site and by hour for wind potential at 80 meters. For every county centroid in the U.S., we find the NREL site closest to the centroid, giving one observation per county per hour. Then we convert wind speed into

an estimated capacity factor by county by hour (ECFH).[42] 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 data (EPA (2014)) indicates which counties actually have wind turbines. We calculate what share of counties with wind turbines that are in each decile. In other words, we determine the probability of building a turbine in each decile (PBTEC). Now using the ECFH, we take the weighted average across a region using PBTEC. This gives us capacity factors at the region hourly level, which we call RECFH. The last step is to compare the predicted capacity factors in the regions for which we have actual capacity factor data for 2019. We calculate the average difference between the 2019 data and the 2014 predictions, by month and hour. Then we add this "bias" back onto the RECFH in regions for which we do not have actual 2019 capacity factor data. Finally these predictions are bounded by zero and one.

O.A.4 Details of the procedure to determine optimized charge profiles

ec:nestmax

In theory, the optimized charge profiles can be found by solving the planner's problem (1) for a given charging profile, computing the appropriate objective (welfare, carbon emissions, or cost of charging electric vehicles) from this solution, and then using an outer numerical optimization algorithm to vary the charging profile until a minimum (maximum for welfare) of the objective is found. In practice, there are two complications.

The first complication is that the outer loop may get stuck in a local minimum and the particular local minimum found may be influenced by both the starting value for the charging profile as well as the convergence tolerances used in the optimization algorithms. To address this issue, we find the (possibly local) minima for three separate sets of starting values and convergence tolerances for each of the 156 parameter cases (13 regions × 2 carbon tax cases × 2 renewable capital cost cases × 3 objectives). This gives us a total of 456 candidate charge profiles. We then do a post-processing step in which we take consider, for each of the

[42] 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.

156 parameter cases, all of the 456 candidate charge profiles and see which one leads to the minimum objective for that case.

The second complication is that the OSQP algorithm we use to solve the planner's problem (1) can occasionally take a long time to converge. This is not much of an issue if we just want to solve the problem for a few different parameters, but becomes troublesome when we imbed the planner's problem in a outer optimization problem that seeks the optimized charge profiles and therefore may solve the planner's problem hundreds or thousands of times. To address this issue, we consider an approximation procedure to find the 456 candidate charge profiles. In particular, we define a modified planner's problem in which the added EV electricity consumption becomes a choice variable rather than an exogenous value $\bar{E}_t$. To keep the actual EV consumption close to the exogenous value we specify an "utility" function for EV electricity consumption as

$$V_t(E_t) = \kappa(E_t - \bar{E}_t)^2,$$

where κ is a large number. The resulting planner's problem is still a quadratic programming problem and almost always converges quickly. After finding the candidate profiles, we use the original planner's problem (1) with exogenous $\bar{E}_t$'s to do the post-processing step.

Online Appendix Tables

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

table-SumStats

Region	Capacity Factors Solar		Capacity Factors Wind		Observed Demand		Observed Price	
West								
California	0.27	(0.33)	0.27	(0.19)	30,187	(6,149)	35.24	(26.21)
East								
Carolinas	0.21	(0.28)	0.27	(0.16)	25,460	(5,442)	25.83	(7.35)
Central	0.24	(0.31)	0.43	(0.20)	30,839	(5,278)	22.56	(32.08)
Florida	0.23	(0.29)	0.19	(0.09)	27,552	(7,239)	19.55	(4.53)
Mid Atlantic	0.19	(0.26)	0.33	(0.22)	91,362	(15,759)	25.47	(20.29)
Mid West	0.18	(0.24)	0.35	(0.19)	80,791	(12,090)	24.85	(17.21)
New England	0.16	(0.24)	0.30	(0.21)	13,503	(2,428)	30.85	(20.29)
New York	0.18	(0.23)	0.31	(0.25)	17,789	(3,198)	25.15	(15.16)
North West	0.27	(0.33)	0.31	(0.15)	39,982	(5,526)	21.13	(21.72)
South East	0.23	(0.30)	0.23	(0.14)	27,762	(5,992)	20.39	(2.39)
South West	0.29	(0.32)	0.38	(0.21)	11,923	(3,406)	27.48	(5.18)
Tennessee	0.21	(0.30)	0.27	(0.18)	18,192	(3,740)	22.13	(8.41)
Texas								
Texas	0.24	(0.31)	0.40	(0.21)	43,798	(9,769)	29.69	(70.63)

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

Table O.A.2: LREC for Flat (24/7) Electricity Use

table-LRME-flat

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.338	0.241	0.192	0.112
Carolinas	0.338	0.338	0.006	0.090
Central	0.338	0.118	0.061	0.049
Florida	0.338	0.331	0.001	0.217
Mid Atlantic	0.338	0.338	0.128	0.096
Mid West	0.338	0.338	0.107	0.081
New England	0.338	0.338	0.024	0.119
New York	0.338	0.338	0.153	0.119
North West	0.338	0.248	0.085	0.059
South East	0.338	0.336	0.001	0.118
South West	0.337	0.179	0.075	0.054
Tennessee	0.338	0.338	0.003	0.102
Texas	0.326	0.143	0.067	0.051

Notes: All hours have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.3: LREC for Daytime Electricity use (8am to 6pm inclusive)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.316	0.075	0.076	0.059
Carolinas	0.332	0.135	0.010	0.040
Central	0.179	0.056	0.034	0.031
Florida	0.106	0.091	-0.083	0.086
Mid Atlantic	0.340	0.152	0.059	0.039
Mid West	0.343	0.179	0.049	0.042
New England	0.337	0.337	0.083	0.066
New York	0.339	0.145	0.046	0.033
North West	0.120	0.084	0.053	0.037
South East	0.128	0.100	-0.079	0.043
South West	0.068	0.025	0.006	0.010
Tennessee	0.338	0.142	0.019	0.049
Texas	0.133	0.023	0.029	0.024

table-LRME-day

Notes: All hours from 8am to 6pm have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.4: LREC for Nighttime Electricity use (7pm to 7am inclusive)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.352	0.365	0.276	0.151
Carolinas	0.343	0.490	0.033	0.131
Central	0.449	0.165	0.080	0.061
Florida	0.520	0.499	0.150	0.318
Mid Atlantic	0.337	0.499	0.182	0.140
Mid West	0.334	0.434	0.146	0.107
New England	0.340	0.340	-0.009	0.162
New York	0.339	0.510	0.239	0.185
North West	0.494	0.360	0.109	0.079
South East	0.508	0.516	0.093	0.178
South West	0.526	0.303	0.123	0.085
Tennessee	0.338	0.485	0.016	0.143
Texas	0.450	0.237	0.091	0.069

table-LRME-night

Notes: All hours from 7pm to 7am have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.5: LREC for Summer Electricity use (May to October)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.322	0.223	0.022	0.018
Carolinas	0.320	0.210	0.176	0.089
Central	0.180	0.104	0.038	0.025
Florida	0.296	0.241	0.243	0.176
Mid Atlantic	0.332	0.233	0.163	0.113
Mid West	0.332	0.260	0.112	0.088
New England	0.313	0.313	-0.047	0.133
New York	0.315	0.232	0.138	0.109
North West	0.174	0.154	-0.016	-0.022
South East	0.271	0.231	0.232	0.145
South West	0.196	0.196	0.089	0.061
Tennessee	0.327	0.211	0.098	0.089
Texas	0.255	0.170	0.065	0.032

table-LRME-summer

Notes: All hours from May to October have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.6: LREC for Winter Electricity use (November to April)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.354	0.264	0.360	0.206
Carolinas	0.356	0.469	-0.164	0.093
Central	0.499	0.135	0.084	0.075
Florida	0.381	0.429	-0.240	0.261
Mid Atlantic	0.344	0.447	0.093	0.080
Mid West	0.344	0.419	0.103	0.081
New England	0.364	0.364	0.096	0.106
New York	0.361	0.445	0.171	0.132
North West	0.503	0.343	0.188	0.144
South East	0.408	0.446	-0.218	0.094
South West	0.486	0.161	0.066	0.050
Tennessee	0.349	0.469	-0.083	0.115
Texas	0.400	0.111	0.070	0.070

table-LRME-winter

Notes: All hours from November to April have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.7: LREC for Summer Day Electricity use (May to October 8am to 6pm)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.291	0.055	-0.053	-0.037
Carolinas	0.311	-0.097	0.247	0.032
Central	-0.033	0.051	0.012	0.009
Florida	-0.074	-0.100	0.395	0.060
Mid Atlantic	0.338	-0.027	0.086	0.042
Mid West	0.337	-0.077	0.041	0.024
New England	0.305	0.305	0.034	0.072
New York	0.310	-0.021	0.032	0.022
North West	-0.073	-0.011	-0.023	-0.010
South East	-0.088	-0.151	0.434	0.049
South West	-0.247	0.149	0.008	0.000
Tennessee	0.328	-0.083	0.159	0.029
Texas	-0.070	0.198	0.019	0.007

table-LRME-summerday

Notes: All hours from May to October from 8pm to 6pm have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.8: LREC for Winter Night Electricity use (November to April 7pm to 7am)

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
California	0.363	0.401	0.477	0.245
Carolinas	0.359	0.554	-0.102	0.129
Central	0.577	0.196	0.105	0.088
Florida	0.458	0.527	0.041	0.370
Mid Atlantic	0.345	0.556	0.145	0.115
Mid West	0.340	0.414	0.136	0.093
New England	0.362	0.362	0.087	0.143
New York	0.358	0.588	0.258	0.197
North West	0.671	0.468	0.231	0.191
South East	0.464	0.525	0.057	0.131
South West	0.571	0.377	0.109	0.068
Tennessee	0.349	0.558	-0.037	0.148
Texas	0.443	0.313	0.093	0.091

table-LRME-winternight

Notes: All hours from November to April from 7pm to 7am have additional electricity demand equal to one percent of average demand. Units are metric tons per MWh of additional electricity demand.

Table O.A.9: LREC for EPRI Charge Profile

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
CAL	0.352	0.312	0.250	0.125
CAR	0.329	0.461	0.046	0.124
CENT	0.448	0.168	0.080	0.060
FLA	0.417	0.519	0.077	0.220
MIDA	0.327	0.382	0.180	0.138
MIDW	0.326	0.369	0.154	0.107
NE	0.334	0.334	0.104	0.151
NW	0.400	0.326	0.107	0.076
NY	0.332	0.339	0.146	0.179
SE	0.391	0.486	0.099	0.152
SW	0.527	0.252	0.116	0.077
TEN	0.328	0.440	0.057	0.142
TEX	0.487	0.187	0.097	0.073

table-LRME-EV-EPRI

Notes: Units are metric tons per MWh of additional electricity demand.

Table O.A.10: LREC for Flat Charge Profile

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
CAL	0.312	0.240	0.198	0.113
CAR	0.327	0.338	0.008	0.092
CENT	0.336	0.118	0.063	0.052
FLA	0.338	0.336	0.006	0.218
MIDA	0.338	0.334	0.130	0.098
MIDW	0.335	0.334	0.110	0.083
NE	0.338	0.337	0.014	0.122
NW	0.338	0.247	0.087	0.061
NY	0.338	0.336	0.100	0.123
SE	0.337	0.337	0.001	0.121
SW	0.337	0.183	0.076	0.055
TEN	0.335	0.336	0.005	0.104
TEX	0.332	0.144	0.069	0.053

table-LRME-EV-Flat

Notes: Units are metric tons per MWh of additional electricity demand.

Table O.A.11: LREC for Carbon Minimizing Charge Profile

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
CAL	-0.164	-0.113	-0.041	-0.007
CAR	-0.040	-0.222	-0.044	-0.023
CENT	-0.114	0.004	0.007	0.005
FLA	-0.202	-0.121	-0.125	-0.168
MIDA	0.217	-0.315	-0.032	-0.032
MIDW	0.308	-0.419	-0.019	-0.014
NE	0.328	0.250	-0.039	-0.018
NW	-0.200	-0.117	0.016	0.010
NY	0.322	-0.266	-0.074	-0.062
SE	-0.137	-0.089	-0.074	-0.055
SW	-0.127	-0.070	-0.053	-0.033
TEN	-0.003	-0.145	-0.087	-0.008
TEX	-0.158	-0.077	-0.012	-0.007

table-LRME-EV-Carbmin

Notes: Units are metric tons per MWh of additional electricity demand.

Table O.A.12: LREC for Welfare Maximizing Charge Profile

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
CAL	-0.088	-0.040	0.081	0.050
CAR	-0.040	-0.159	0.027	0.019
CENT	-0.067	0.040	0.045	0.046
FLA	-0.202	-0.103	0.007	-0.012
MIDA	0.328	-0.315	0.061	0.031
MIDW	0.328	-0.378	0.084	0.045
NE	0.339	0.338	-0.035	0.107
NW	-0.138	-0.070	0.046	0.031
NY	0.337	-0.200	0.024	0.019
SE	-0.117	-0.084	0.018	0.039
SW	-0.086	-0.060	0.009	-0.003
TEN	0.097	-0.079	0.029	0.047
TEX	-0.094	-0.077	0.023	0.015

table-LRME-EV-Welmax

Notes: Units are metric tons per MWh of additional electricity demand.

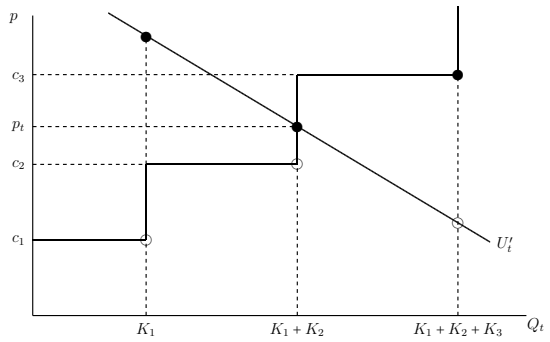
Table O.A.13: LREC for Charge Cost Minimizing Charge Profile

Region	BAU		Pigouvian	
	High Cost	Low Cost	High Cost	Low Cost
CAL	0.311	0.126	0.086	0.055
CAR	0.341	0.270	0.029	0.030
CENT	0.414	0.109	0.054	0.043
FLA	0.409	0.196	-0.002	0.014
MIDA	0.336	0.368	0.080	0.045
MIDW	0.334	0.409	0.091	0.058
NE	0.339	0.338	-0.027	0.111
NW	0.346	0.100	0.049	0.034
NY	0.338	0.346	0.080	0.021
SE	0.388	0.181	0.009	0.039
SW	0.186	0.016	0.010	0.010
TEN	0.337	0.300	0.024	0.048
TEX	0.326	0.067	0.034	0.026

table-LRME-EV-Chargemin

Notes: Units are metric tons per MWh of additional electricity demand.

Online Appendix Figures

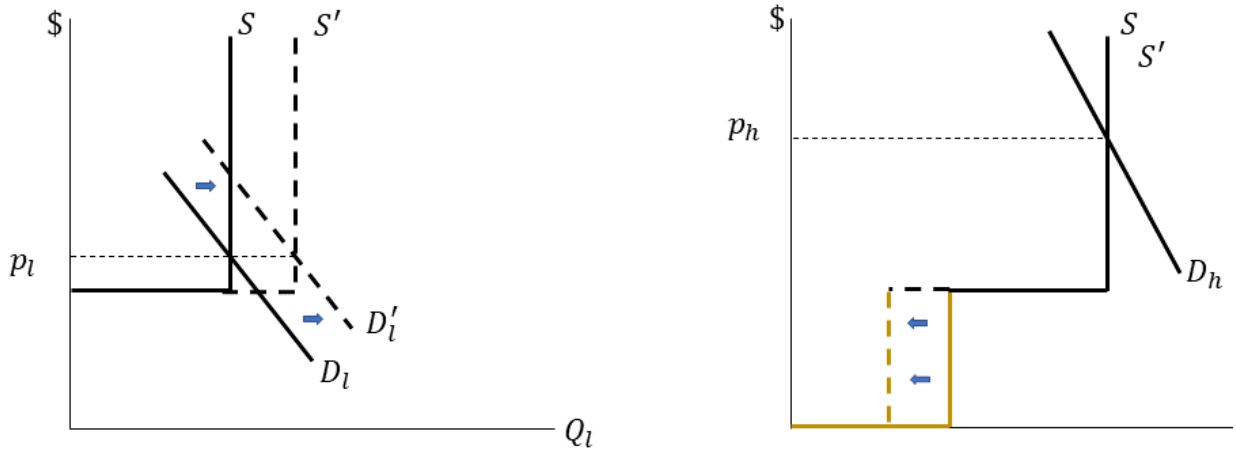


Graph

Figure O.A.1: Illustrative supply and demand with market clearing price p_t.
Notes: To illustrate Lemma 2, this figure assumes no storage and three technologies with capacity factors equal to one and no electrification. 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

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

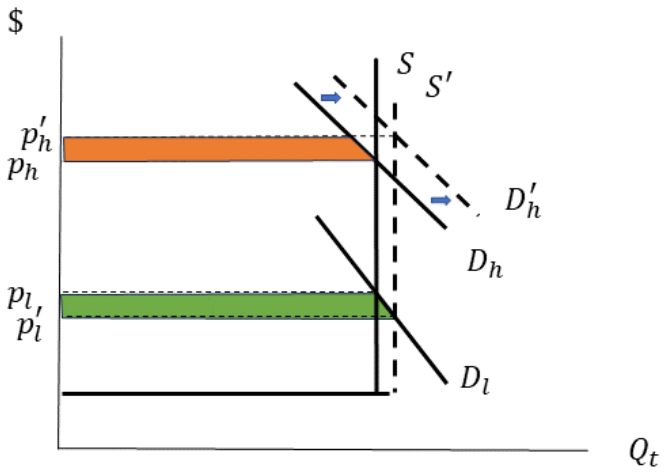
which is the minimum of three max expressions. The solid and unfilled circles indicate the values to be compared inside each of the max expressions, with the solid circles indicating the resulting maximum values. Thus $p_t = \min\{U_t'(K_1), U_t'(K_1 + K_2), c_3\}$, i.e., the minimum over the solid circles. 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. $p_t = U_t'(K_1 + K_2)$.



es_DloadRen

Figure O.A.2: Illustration of Result 2.

Notes: Two periods: h and l, and two technologies: intermittent renewable (1, yellow) and dispatchable fossil (2, black). Renewable produces only in period h. Equilibrium prices are given by $p_h = r_1$ and $p_l + p_h = 2c_2 + r_2$. Demand growth in period l increases gas capacity and decreases renewables, which is Result 2.



fig_Res_CS

Figure O.A.3: Illustration of Result 3.

Notes: Two periods: h and l, and one technology with prices given by $p_l + p_h = 2c_1 + r_1$. Demand growth in period h increases p_h which decreases consumer surplus to the existing consumers by the orange trapezoid. Because $\Delta p_h = -\Delta p_l$, the existing consumers gain the green consumer surplus in period l. The gain (green trapezoid) exceeds the loss (orange trapezoid), thus demand growth increases consumer surplus for existing consumers, which is Result 3.

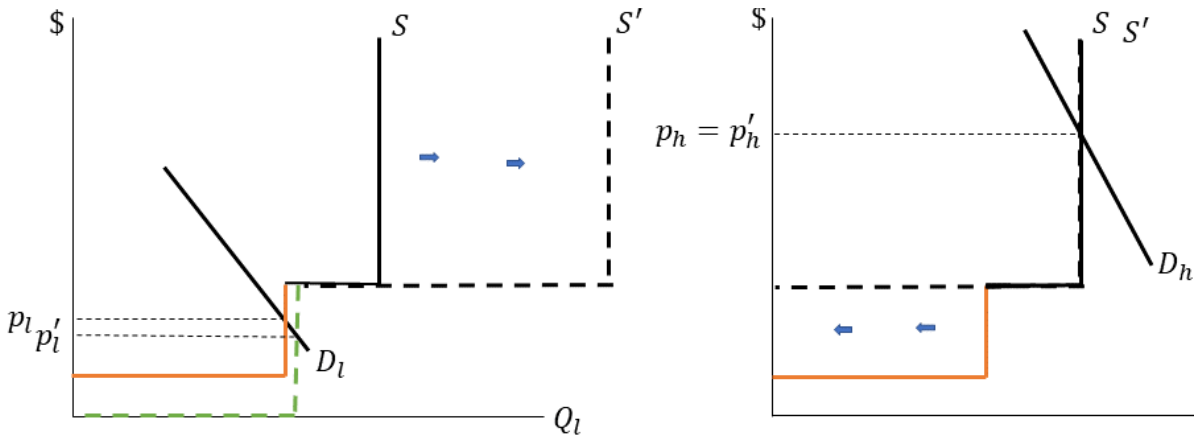


Figure O.A.4: Illustration of Result 4.

Notes: Two periods: h and l, and three technologies: intermittent renewable (1, green), nuclear (2, orange) and fossil (3, black). Renewable produces only in period l. High renewable cost has supply S from nuclear and fossil in both periods with prices $p_l + p_h = 2c_s + r_2$ and $p_h = c_3 + r_3$ and $p_l < r_1$. Low renewable cost has dashed supply S' with prices $p_l' = r_1 < p_l$ and $p_h' = p_h$. Low renewable cost drives out nuclear capacity, which increases capacity of fossil and increases emissions, which is Result 4.

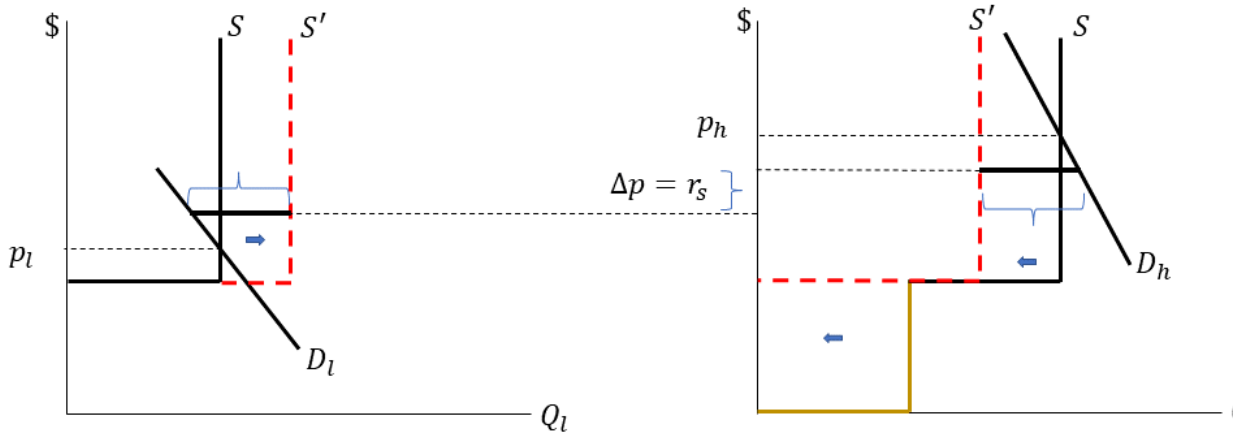


Figure O.A.5: Illustration of Result 5.

Notes: Two periods: h and l, and two technologies: intermittent renewable (1, yellow) and fossil (2, black). Renewable produces only in period h. Initially, r_s is large enough that there is no storage. The equilibrium has supply S and implies prices given by $p_h = r_1$ and $p_l + p_h = 2c_2 + r_2$. Cheaper storage narrows the price gap which drives down p_h and causes renewables to exit resulting in supply S' entirely from fossil. Battery charge/discharge is indicated by heavy, horizontal line. Thus cheaper storage drives out renewables, which is Result 5.

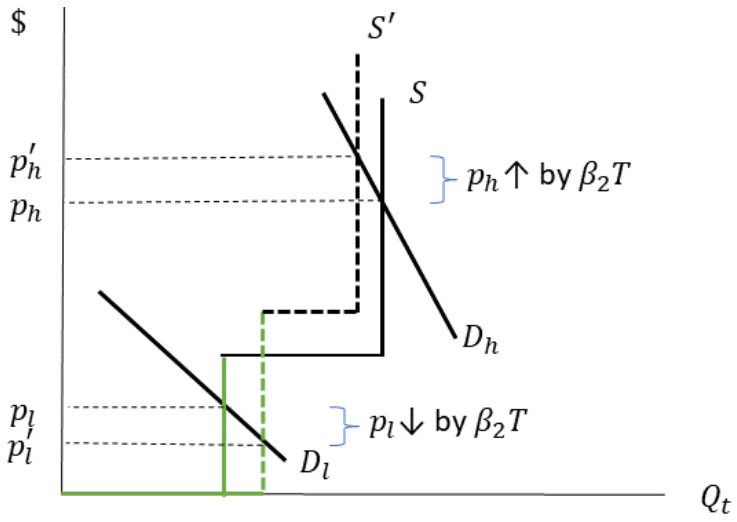


Figure O.A.6: Illustration of Result 6.

Notes: Two periods: h and l, and two technologies: renewable (1, green) and gas (2, black). Without carbon tax, supply is S, and prices are $p_l + p_h = r_1$ and $p_h = c_2 + r_2$. With a carbon tax T, supply is S', and prices are $p_l' + p_h' = r_1$ and $p_h' = c_2 + \beta_2 T + r_2$. Carbon tax increases gas cost and reduces emissions. Whether the carbon tax increases or decreases electricity use depends on the relative slopes of D_l and D_h.

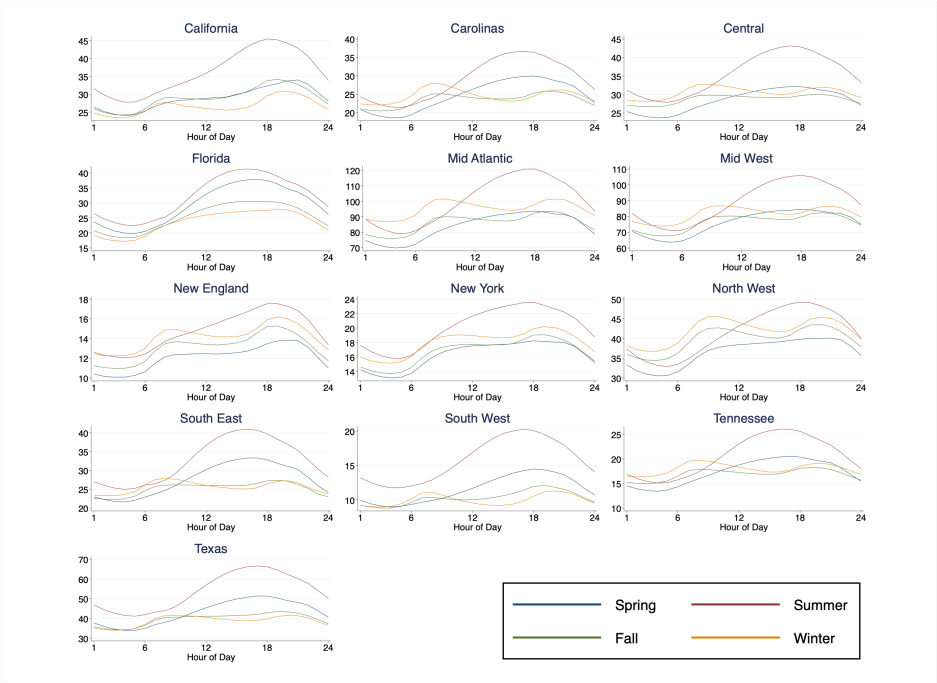


Figure O.A.7: Mean hourly observed demand by season and hour of day for each EIA region.

Notes: Demand in thousands of MWh.

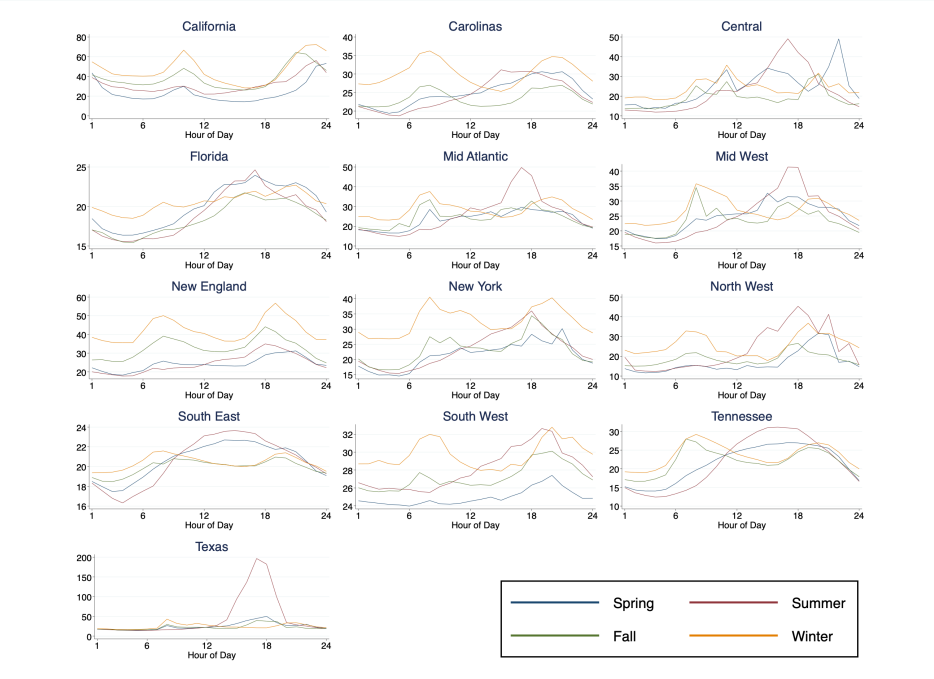


Figure O.A.8: Mean hourly observed price by season and hour of day for each EIA region.

fpriceMulti

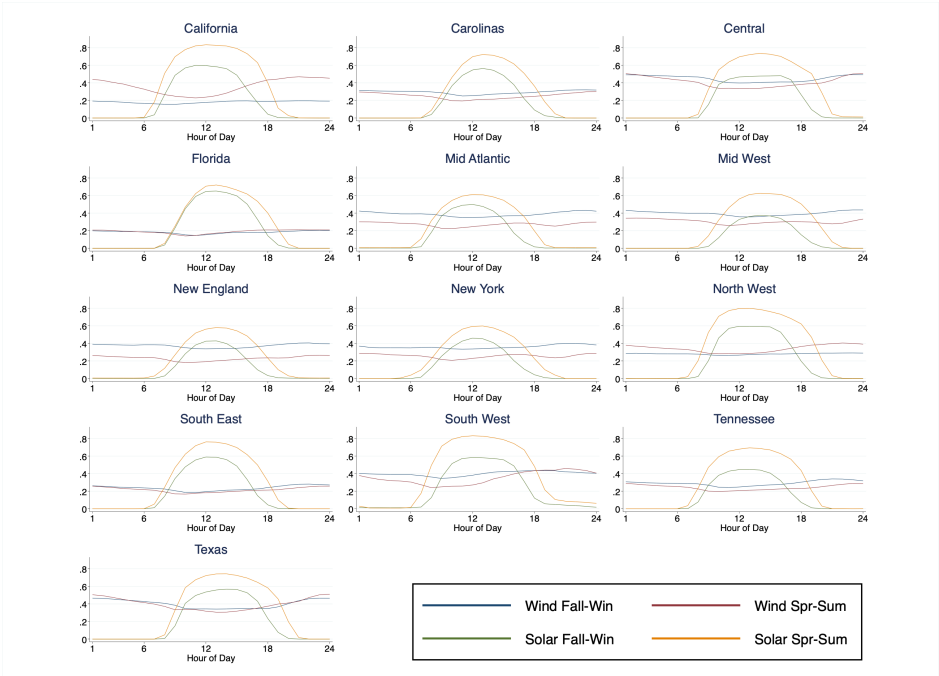
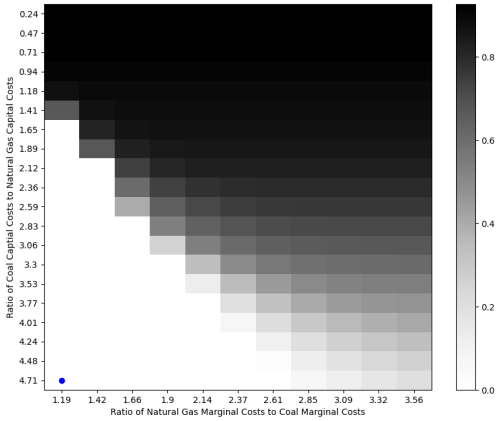


Figure O.A.9: Mean hourly capacity factors by season and hour of day for each EIA region.

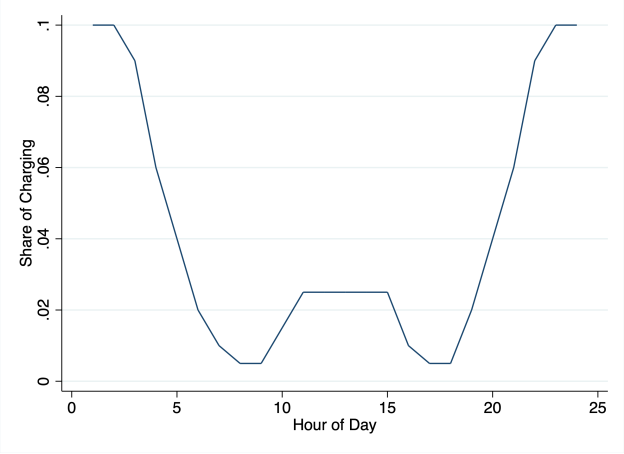
fig_cfMulti



_plot_coal

Figure O.A.10: Coal generation sensitivity analysis.

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



fig_epri

Figure O.A.11: EPRI charging profile.