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 change 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`.

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

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

1 Introduction

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

This paper constructs a framework for analyzing a completely transformed electricity grid with a long-run competitive equilibrium model of electricity consumption, generation, investment, and storage.[2] There are three key distinguishing features of our work. First, in our model, entry and exit for all technologies respond to the interconnected feedback effects from carbon policy, technological innovation and electrification, free from the hysteresis of legacy investments and historical accidents.[3] Second, we use the model to derive several theoretical possibilities, and our calibration allows us to test the degree to which these possibilities have practical relevance. Third, the model and calibration allow us to calculate the effects of increasing demand for electricity on emissions for a variety of different electrification scenarios.

[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)

The long-run theoretical possibilities can differ in surprising ways from their short-run analogs. In the short run, an increase in electricity consumption due to electrification leads to a non-negative change in generation from renewables. In the long run, however, electrification can lead to a decrease in generation from renewables due to a crowding out of renewable investment. Similarly, in the short run, electrification leads to a non-negative change in emissions. In the long run, however, electrification can lead to a *decrease* in emissions if electricity usage in some periods induces entry of renewables which offset fossil generation in other periods. In this case, electrification can actually facilitate decarbonization of the electricity grid. These theoretical possibilities illustrate the importance of our long-run perspective.

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

In addition to wind and solar, our calibration includes nuclear power, two natural gas powered technologies, and battery storage.[4] Generation from hydro power plants is considered to be exogenously fixed at historical levels. All capital cost estimates are for the near future, and because these costs are particularly uncertain for renewable technologies, we consider a range of renewable capital costs. According to our calculations in Section 3,

[4]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.

new coal plants are dominated by natural gas plants. Because there are no fixed inputs in the long run, we do not analyze any existing plants.[5]

Electrification will affect renewable capacity, and our theoretical results show that this may help or hinder decarbonization. To study this relationship, we simulate the effects of both small and large changes in electricity demand on the long-run equilibrium and emissions. We define the long-run emissions change (LREC) as the change in emissions normalized by the change in electricity demand.[6] For small demand changes, there are generally three types of outcomes. First, the demand change may simply increase natural gas capacity so that the LREC is approximately equal to the natural gas power plant emissions rate. Second, the demand change may decrease renewable capacity so that the LREC is greater than the natural gas rate. Third, the demand change may increase renewable capacity so that the LREC is less than the natural gas rate and may even be zero or negative. These effects vary across locations and hours; negative LRECs occur mostly when demand changes are in the daytime hours.

The effects of large changes in electricity demand on emissions also depend on where and when the electricity is used.[7] For transportation, this means the hours the electric vehicles (EVs) are charged, *i.e.,* the charging profile. We find that, for a profile with mostly nighttime charging and baseline renewable capital costs, electrifying 100% of car vehicle miles traveled (VMT) would result in a 23% increase in electricity-sector carbon emissions.[8] We also determine regional-specific charging profiles that are optimized with respect to various objectives such as minimizing carbon emissions and maximizing social welfare. The carbon minimizing charging profiles generally feature charging during the day. Remarkably, if renewable capital

[5]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.

[6]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 emission 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 because we consider both small and large changes in electricity demand.

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

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

costs are at the low end of the range we consider, the carbon minimizing charging profiles lead to *negative* LRECs. In other words, charging EVs with these profiles can completely decarbonize passenger vehicle transportation and reduce carbon emissions from the electricity sector, because they induce a dramatic entry of renewables. The welfare maximizing charging profile balances emissions reductions with private surplus losses and reduces total carbon emissions substantially. These charging profiles generally feature significant charging during the day as well.

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 uniquely suited to analyze.

In addition to these results on long run emissions, another major contribution of our paper is the transparency, tractability, and flexibility of our long run model. As such, it provides a valuable complement to existing methodologies. Large multi-sectoral models such as the National Energy Modeling System (NEMS) or the models in the Princeton Net-Zero America Report can provide a comprehensive basis for policy analysis but allow for limited theoretical insights (Palmer et al. (2011), Gillingham et al. (2021), Stock and Stuart (2021), and Gagnon and Cole (2022)). Cost-minimizing grid dispatch models may allow for complex ramping and transmission constraints, but do not generally analyze welfare effects (Hawkes (2014), Raichur et al. (2015)). Although it is beyond the scope of this paper, our model is well suited to study, for example, the effects of decarbonization policy such as subsidies for renewable generation.[9] We expect it will provide new insights into these issues.

[9]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

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 $U_t'(D_t(p)) \equiv p$.[10] 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.

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).[11] 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 $S_t = S_{t-1} + b_t$.[12] Battery storage cannot exceed the

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.

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

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

[12] 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.

maximum battery capacity K_s, so the state of the battery must satisfy $0 \le S_t \le K_s$. The battery capacity is endogenous in the model and has capital costs r_s per unit. Electricity balance in each hour requires that $Q_t + \bar{E}_t + b_t \le \sum_i q_{it}$, 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.[13] 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

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.[14]

The Kuhn-Tucker first-order conditions include

$$\begin{array}{rrccl}
Q_t \ge 0 & d\mathcal{L}/dQ_t = U_t'(Q_t) - p_t \le 0 & \forall t & C.S. & (3) \quad \text{eq:FOCQ} \\
q_{it} \ge 0 & d\mathcal{L}/dq_{it} = -c_i + p_t - \lambda_{it} \le 0 & \forall i, t & C.S. & (4) \quad \text{eq:FOCq} \\
 & d\mathcal{L}/db_t = -p_t + \phi_t = 0 & \forall t & & (5) \quad \text{eq:FOCb} \\
S_t \ge 0 & d\mathcal{L}/dS_t = \phi_{t+1} - \phi_t - \mu_t \le 0 & \forall t & C.S. & (6) \quad \text{eq:FOCS} \\
K_i \ge 0 & d\mathcal{L}/dK_i = \sum_t \lambda_{it} f_{it} - r_i \le 0 & \forall i & C.S. & (7) \quad \text{eq:FOCK} \\
K_s \ge 0 & d\mathcal{L}/dK_s = \sum_t \mu_t - r_s \le 0 & & C.S., & (8) \quad \text{eq:FOCbarS}
\end{array}$$

[13] 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.

[14] H_t is not technically the Hamiltonian of (1) because it treats the adjoint variable differently.

where $C.S.$ indicates a complementary slackness condition.[15] The condition [3] implies that the marginal benefit equals the shadow value p_t if electricity consumption is positive. From here on p_t is called the *electricity price*.

The following lemmas 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 $p_t = \min_i \{\max\{c_i, U_t'(\sum_{i' \leq i} f_{i't} K_{i'} - b_t - \bar{E}_t)\}\}$.*

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.

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

The long-run competitive equilibrium, characterized by these lemmas, may not be efficient because of the external costs from carbon emissions. Accordingly, 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 of electrification.

Long-run effects can differ from their short-run analogs in which capacities are fixed. The following results illustrate some of the counter intuitive possibilities which can occur in the long run. The first set of results focus on *electrification*, which we define as an increase (typically from zero) $\Delta \bar{E}_t$ for some t. 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 $\Delta \bar{E}_t$. The long run emissions change (LREC) from electrification is defined as the increase in emissions normalized by the increase in electricity consumption:

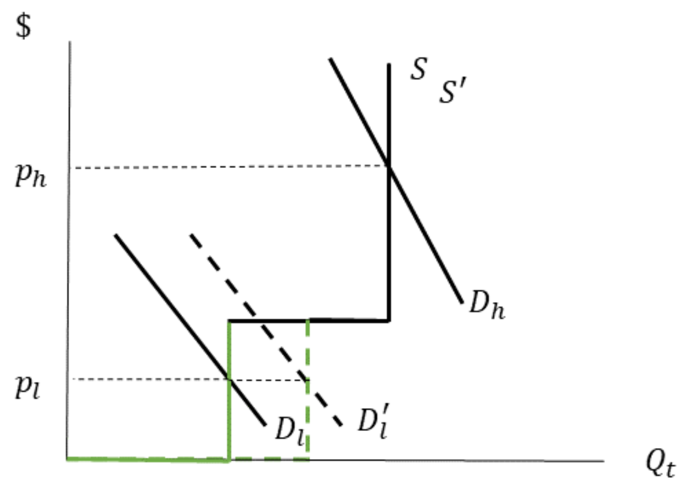
$$\text{LREC} = \frac{\sum_i \sum_t \beta_i \Delta q_{it}}{\sum_t \Delta \bar{E}_t}.$$

In the short run, electrification increases emissions if increased electricity is supplied by a polluting source. At best, the short run effect could be zero if, for example, the increased electricity is supplied by renewables. In contrast, the following result shows that electrification can *decrease* emissions in the long run.

res:Dload **Result 1.** *Electrification can decrease carbon emissions.*

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. Conversely if the marginal technology is dirty, carbon emissions will increase, in line with short run intuition. But, because the additional dirty capacity may be used in other periods, carbon emissions may increase by more than the emissions rate of the marginal technology.

Figure 1 illustrates the proof. There are two time periods and two generating technologies: technology 1 is renewable with zero operating costs and technology 2 is fossil with



_Res_Dload

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.

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.[16] Electrification increases demand in the low demand period, equilibrium prices are unchanged, and 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 in the high demand period decreases, and that reduces carbon emissions.

Although Figure 1 shows a case in which electrification leads to additional renewable capacity, it is possible for the opposite to occur, as stated in the next result.

s:DloadRen **Result 2.** *Electrification can decrease renewable capacity.*

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 used in other periods, which may crowd out renewables. Graphical illustrations of this result and all subsequent results are given in the Online Appendix Figures O.A.2 to O.A.6.

[16] 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 short run, an increase in demand will increase prices and lower the consumer surplus of the existing consumers. This may be reversed in the long run.

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

Electrification in one period will lead to an increase in capacity of the technology on the margin in that period and possibly a higher price. But this capacity may lower prices in other hours, and on net the benefits of lower prices may outweigh the costs of the higher price for existing consumers.

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 may increase. If electrification leads to an increase in emissions, then the emissions increase under high renewable capital costs may be smaller than the increase in emissions under low capital costs.*

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

The final two results present counter-intuitive results about storage costs and carbon taxes. They illustrate the variety of issues for which analytical results can be obtained in our model.

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

Although it may seem intuitive that battery storage may result in more renewables, Result 5 shows that this is not necessarily the case.[17] If intermittent renewables generate electricity in high-price periods, then storage will reduce their profitability.[18]

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 may increase i.e., $\sum_t \Delta Q_t > 0$.*

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

[18] 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.

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

The model 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.

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).[19] 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 that is independent of demand in other hours. Each hourly demand function is parameterized

[19] 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.

by the observed consumption and price and an assumed elasticity of -0.15 at the observed consumption-price pair.[20]

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.

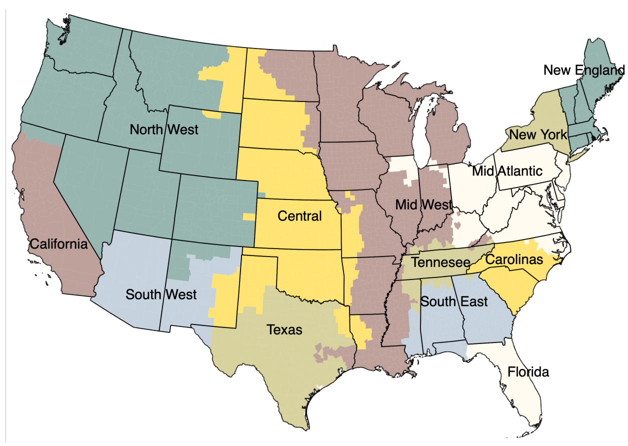


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Figure 2: Map of EIA regions.

[20] 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. Baseline operating and capital costs, shown in Table 1, for the five technologies and for grid-scale battery storage are from USEIA (2021). 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

able-CapOpCosts

	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 an alternative specification in which the capital costs of renewables are 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 the 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.[21] 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.

The non-renewable technologies in Table 1 are all dispatchable. Advanced nuclear also has zero emissions but slightly higher operating costs and much higher capital costs than renewables. Nuclear may appear to be dominated by renewables based on these costs, but because of the 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. In the BAU cases below, we assume the operating costs are as in Table 1. In 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 from gas, our carbon tax simulations can be reinterpreted as sensitivity of our results to the price of natural gas.[22]

[21] 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.

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

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. Generation from hydro is considered to be exogenously fixed at 2019 levels.

Battery storage is assumed to have no operating cost (no 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

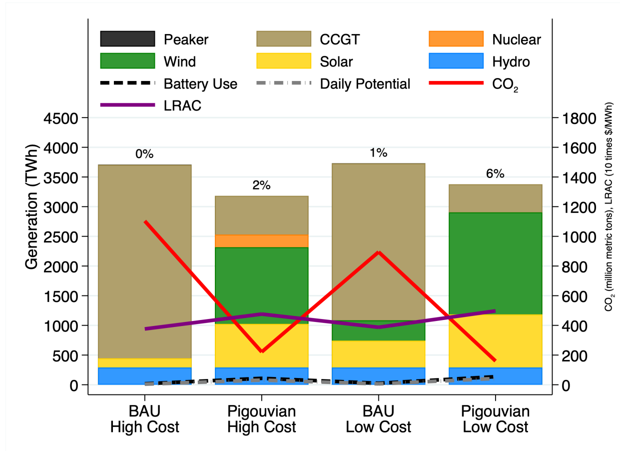
Because the demand curves are linear, the benefit functions $U_t(Q_t)$ are quadratic. Thus the planner's problem in (1) is a quadratic program, and we solve it directly using a publicly available algorithm described in Stellato et al. (2020).[23] This quadratic programming algorithm allows the objective 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 as well as 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 on renewable costs, 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 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.

Before analyzing electrification, we first present the long-run equilibrium without electrification where $\Delta \bar{E}_t = 0$ for each t. Figure 3 summarizes annual generation, carbon emissions,

[23]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.

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.[24] This difference arises because there is no modeled coal generation and because modeled electricity consumption is slightly lower than actual.[25] Imposing the first-best carbon tax (Pigouvian High Cost) reduces emissions dramatically to 221 mmt, and results in significant 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 that a carbon tax could increase electricity consumption, but here electricity consumption (generation) is lower in the Pigouvian cases than in the BAU cases.[26]

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

[25] 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.

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

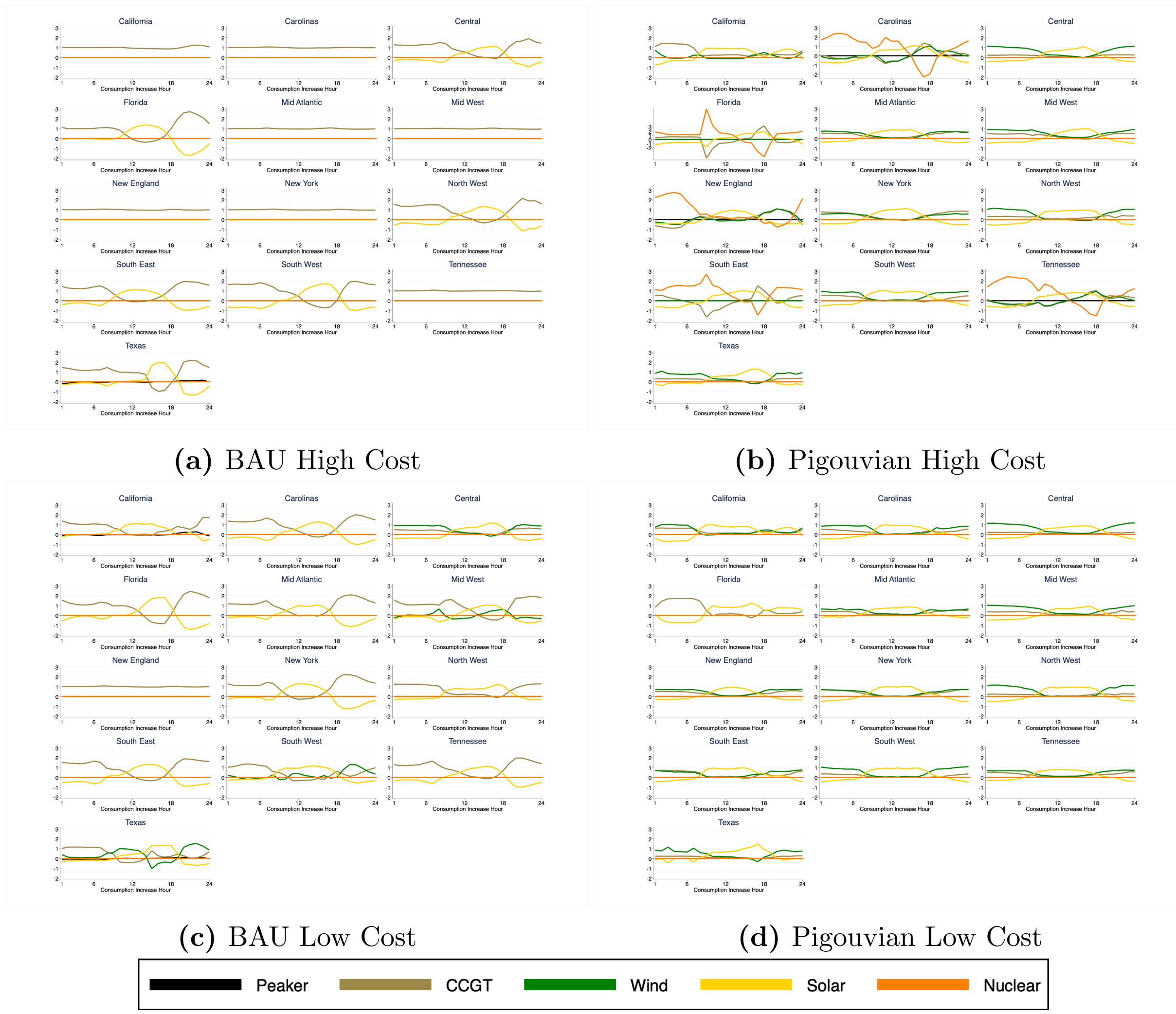
The battery statistics in Figure 3 include Battery Use (sum of charges added to battery in TWh) and Daily Potential (battery use if battery is fully charged and discharged once a day). By either measure battery storage plays a small role. Batteries are most important in Pigouvian Low Cost. However, even 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.

By increasing electricity demand, electrification may increase prices in some hours and induce capacity expansion in the long run. The additional capacity may directly affect emissions and can potentially lower prices and increase electricity consumption in other hours. To analyze these complex interactions, we first model small-scale electrification and then model large scale electric vehicle (EV) adoption.

4.1 Small-scale electrification

To analyze small-scale electrification, we begin with simply hourly scenario in which electrification increases consumption of electricity in a single hour of the day in each day of the year. In particular, for a given hour of the day h, the increase in consumption is equal to one percent of observed average hourly consumption in that region, i.e., if $\bar{Q}$ is average consumption, $\Delta\bar{E}_t = 0.01\bar{Q}$ for every t such that t modulo 24 is h. The effects of this change in consumption on generation and emissions will in general not be isolated to the given hour. For example, an increase in consumption at noon could lead to the entry of solar, which would also generate electricity in other hours besides noon and perhaps crowd out gas generation. So we calculate changes in generation and emissions over all hours of the year.

The results for electrification in each hour of the day are shown in Figure 4. In BAU High Cost, Figure 4 (a), there are seven regions in which electrification in any hour of the



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

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

RME_Decomp

Figure 4: Change in generation by technology and region

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.

day simply leads to a 1:1 increase in generation from combined cycle natural gas.[27] 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 counter intuitive 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 that extra capacity can generate electricity in other hours, which displaces solar in those hours.

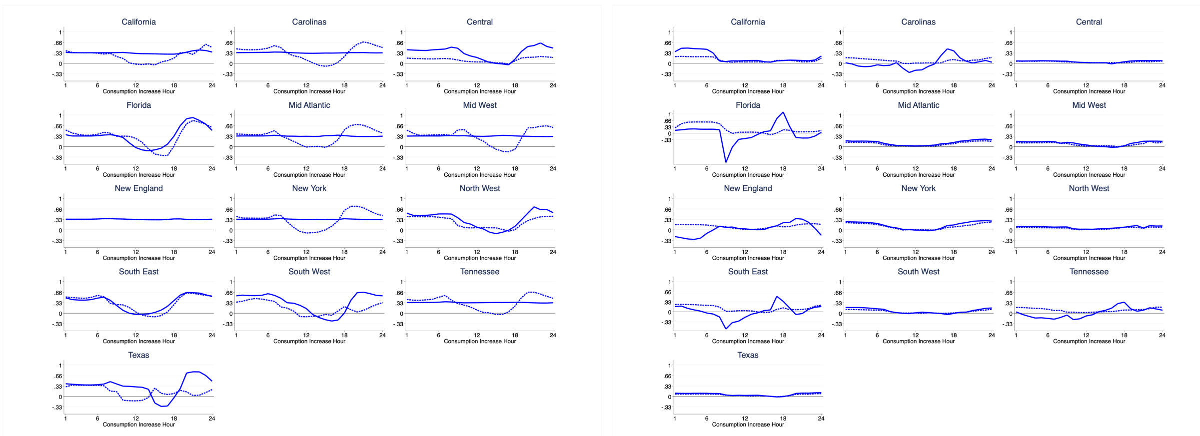
[27]The seven regions are Carolinas, MidAtlantic, MidWest, New England, New York, Tennessee, and California.

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 emissions effects of electrification.

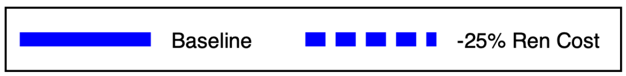
Figures 4 (b)-(d) show an even richer set of responses to electrification. In Pigouvian High Cost, a significant share of generation is nuclear in regions with limited renewable availability, and Figure 4 (b) shows nuclear generation responds to electrification in the long run. For example, in Florida, 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.

The changes in generation are useful to illustrate the mechanisms at work in our long run model. But ultimately we are interested in emissions. Figure 5 aggregates the changes in generation to give the long run emission change (LREC) due to electrification in hour h. In 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) BAU **(b)** Pigouvian



fig_LRME

Figure 5: LREC from electrification in each 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.

(a) solid line). In the other six regions, the LRECs 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. 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 effect is consistent with Result 1 showing that electrification can decrease emissions.

With lower cost renewables, Figure 5 (a) dashed line, the effect during the afternoon is more likely to be below 0.34, e.g., in Carolinas. Thus, cheaper renewables can decrease the emissions from electrification. However, in the evenings, the cheaper renewables actually *increase* the emissions from electrification in some region, e.g., Carolinas. This is consistent with Result 1 showing that the emissions effect of electrification can be higher with lower cost renewables.

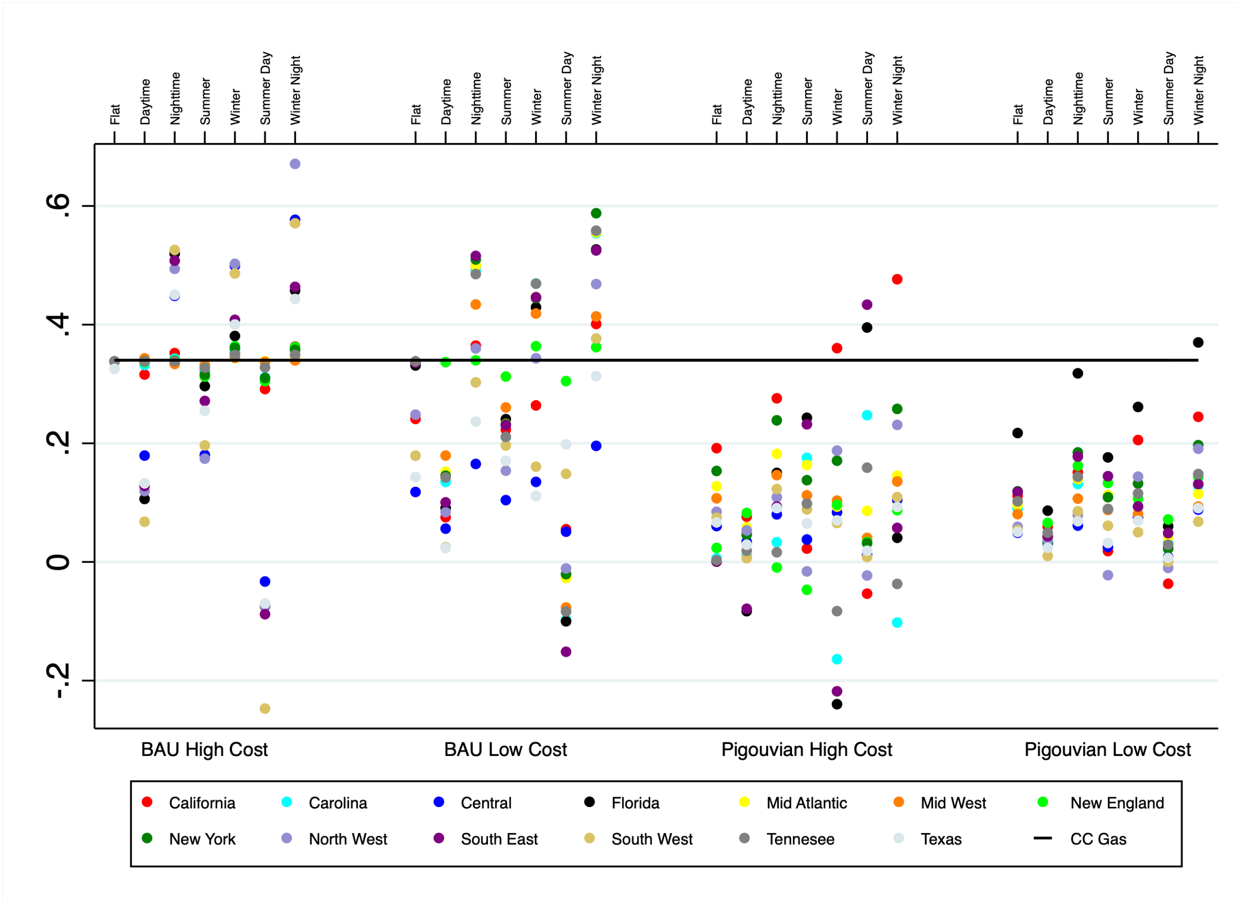
Figure 5 (b) shows the LRECs from electrification under a Pigouvian carbon tax. In general, the LRECs are lower and are close to zero across all hours in some regions, e.g., Central, MidAtlantic, MidWest, Northwest, and Texas. However, in some regions for some hours, the LRECs may exceed 0.34, e.g., California in the early morning, or can be negative. 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 environmental effects from electrification in a given hour. However, they may be of limited use for policy analysis because most electrification uses electricity more than one hour per day. Aggregating these effects across hours may not be reliable because additional generation capacity can be used in many hours.[28]

To analyze more realistic 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 profile in which each hour of the year receives the 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.

Figure 6 shows the LREC per MWh for each of these electrification profiles for the thirteen regions. Two reference levels are zero and 0.34 mt per MWh, which is the emissions rate of 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. Second, LRECs tend to be lower in Daytime (compared to 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, and its effects can be substantial. 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

[28] 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.



ll_seasons

Figure 6: LREC 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.

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.[29]

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).[30]

Figure 7 summarizes the generation, emissions, and battery statistics for Baseline without EVs as well as 100% EV adoption under the various charging profiles.[31] Consider first the BAU High Cost case. Under the EPRI charging profile, using EVs for 100% of light-duty VMT 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. So EV adoption substantially reduces carbon emissions from transportation. Also note that EV adoption *reduces* long-run renewable generation, which is an illustration of Result 2. The

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

[30] 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.

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

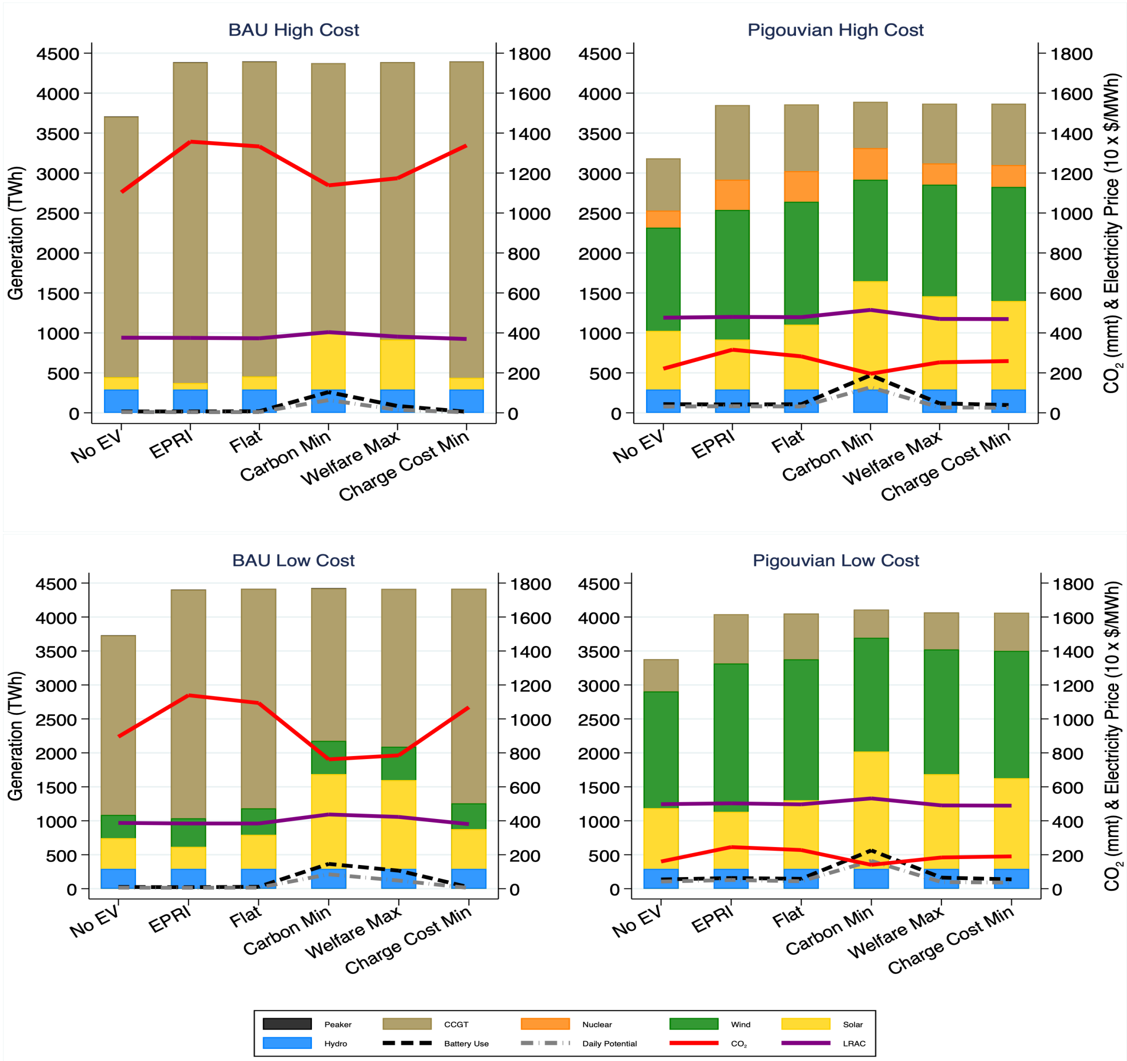
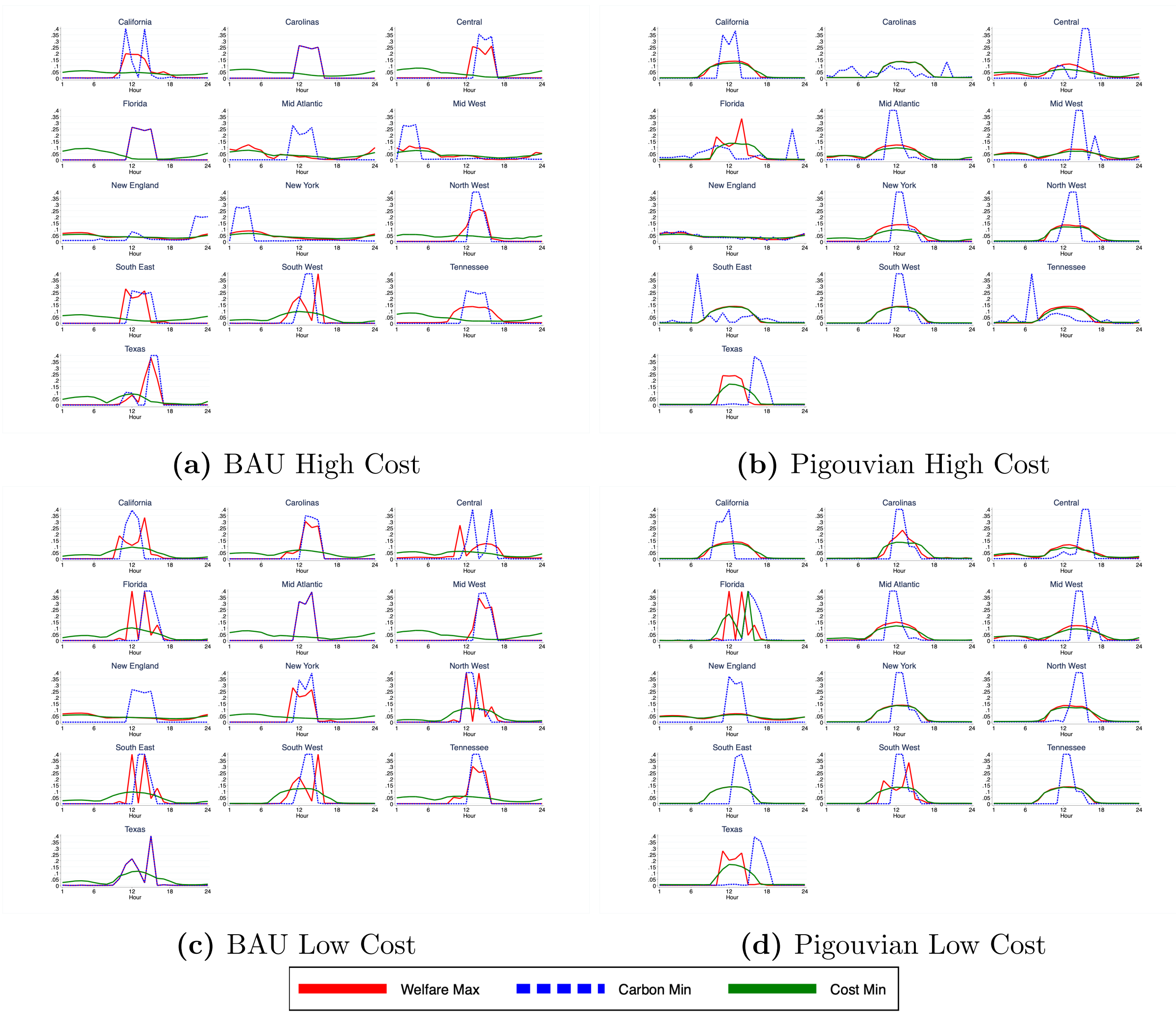


Figure 7: Effects of 100% EV adoption for Different Charging Profiles

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.

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. It also leads to a rather dramatic increase in battery storage. The carbon minimizing charging profile concentrates charging in a few hours, which greatly increases prices during those hours. This in turn 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. One important difference, however, is that there is a *negative* change in emissions when moving from baseline to 100% EV adoption under the Carbon Min profile. For example, in the BAU Low Cost case, the Carbon Minimizing profile leads to emissions that are 132 mmt lower than baseline. This striking result shows that it is possible to completely electrify vehicle transportation while also reducing electricity-sector carbon emissions.[32]



(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.

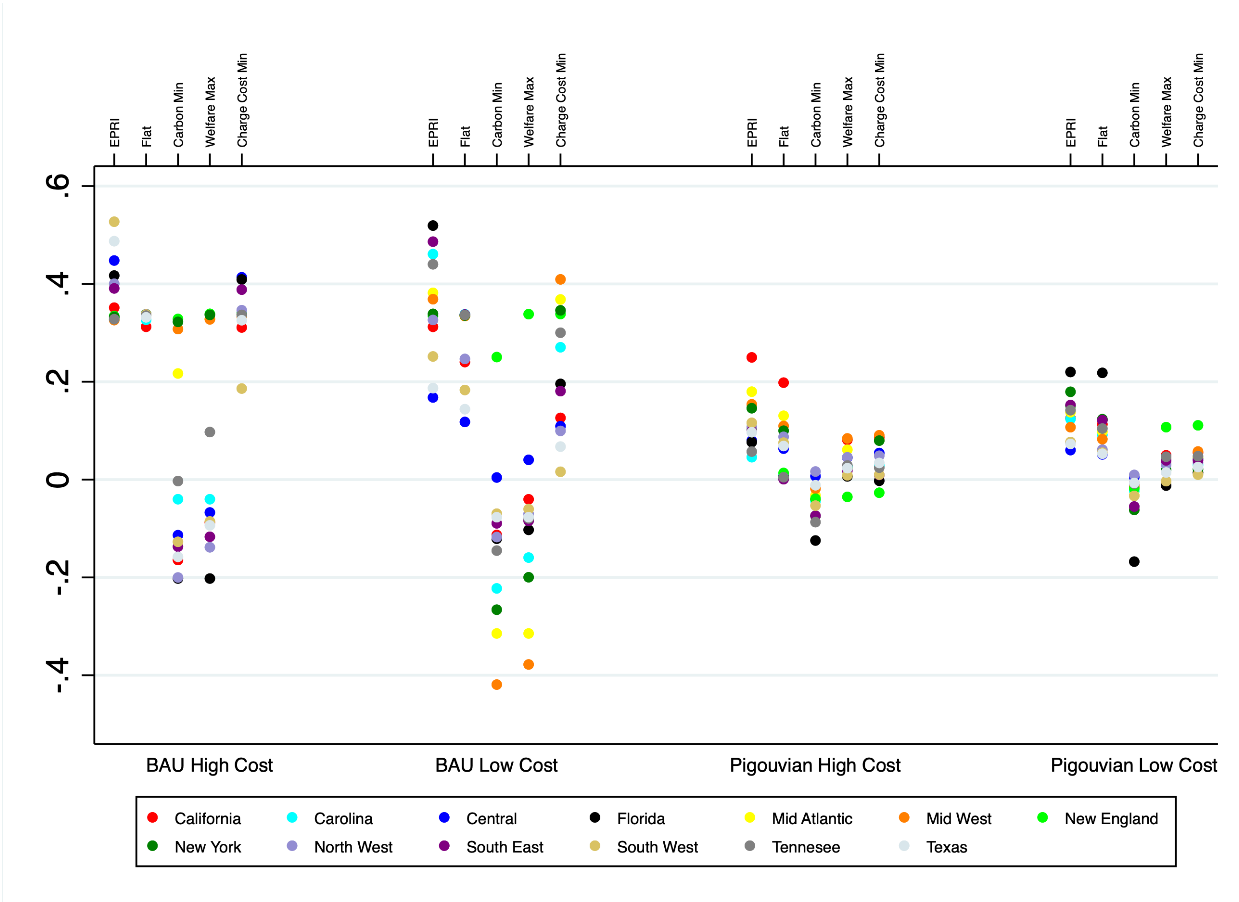
The comparisons across the profiles suggest a tension between the environmental effects and the cost and convenience of charging. Figure 8 shows the optimized charging profiles

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

for each region. In the BAU High Cost, the Cost Min profile spreads charging across many 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.[33]

We conclude the analysis of EV adoption by providing disaggregated information about emissions. The LRECs across regions and charging profiles are shown in Figure 9. For the 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 Carbon Min and Welfare Max have much lower LRECs, including negative LRECs across most (but not all) regions. 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. With carbon pricing, the differences across regions and across charging profiles are much smaller. In particular, the differences between Welfare Max and Charge Cost Min are much smaller, and the LREC are close to zero for most regions.

[33]Intuitively, with carbon pricing, the shadow cost of a unit of charging in a given period is the price in that period which suggests that welfare is maximized by charging in low price periods. Similarly, charging costs are minimized by charging during periods with low prices.



boncompare

Figure 9: LREC 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.

5 Conclusion

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

Our theoretical model demonstrates that several surprising long-run effects are feasible with regards to electrification. Expected electricity demand growth (for example, due to greater EV penetration) could potentially decrease total emissions in the electricity sector. Using simulations from our calibrated model, we show that this is feasible if EV charging is done in a way that minimizes emissions. Depending on the region, this generally involves EV charging in the daytime. Adoption of charging stations in shopping centers and workplaces may facilitate this. Current charging patterns are mostly in the evening, and this leads to greater use of fossil fuels and a crowding out of renewables in the long run. There are important regional exceptions, however, to this general rule, which illustrate the complicated long run interactions between electrification and other policies such as a carbon taxes.

Negative emissions are a tantalizing prospect, however this 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 from EVs and consumer preferences for charging times along with a detailed analysis of welfare from existing light-duty vehicles (consumer surplus from gas vehicles, operating costs, capital costs, and externalities from driving gasoline vehicles).

Although it is known that the environmental effects of electric vehicle adoption depend on the timing of charging (Holland et al. (2022)), our results, taken in conjunction with this previous literature, show that these effects also depend on the time horizon of the analysis. In the short run, the emissions-minimizing time to charge is when renewables are curtailed or when coal is less likely to be on the margin. In the long run, charging only during times with high renewable capacity factors induces entry and may result in negative emissions from the grid. 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 counter productive 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. Similarly, we ignore learning by doing, scale economies, and additional market failures such as learning spillovers and information asymmetries. Additionally, legacy technologies and transition costs may play a role in the feasibility of grid investments. More detailed demand calibrations and modeling of transmission congestion are important possible extensions of our work. Finally, actual solar and wind generation data for several missing regions would allow better capacity factor estimates. Given these caveats, our theoretical and calibration results provide important insights into 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 utilitized).

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

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[34] shows that $\lambda_{it} = \max\{p_t - c_i, 0\}$. Substitution 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 $p_t = c_i$.[35]

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

[34]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.

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

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 $\beta_2 K_2$.

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., $\beta_2 \Delta K_2 < 0$.■

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. ■.

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.

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 $\beta_3 \Delta K_3 > 0$. Thus the emissions increase is larger 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.■

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

endix-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).[36] 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

[36]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: Long Run Marginal Emissions 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: Long Run Marginal Emissions for Daytime Electricity use (8am to 6pm inclusive)

table-LRME-day

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

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: Long Run Marginal Emissions for Nighttime Electricity use (7pm to 7am inclusive)

table-LRME-night

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

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: Long Run Marginal Emissions for Summer Electricity use (May to October)

table-LRME-summer

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

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: Long Run Marginal Emissions for Winter Electricity use (November to April)

table-LRME-winter

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

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: Long Run Marginal Emissions for Summer Day Electricity use (May to October 8am to 6pm)

table-LRME-summerday

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

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: Long Run Marginal Emissions for Winter Night Electricity use (November to April 7pm to 7am)

table-LRME-winternight

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

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.

Online Appendix Figures

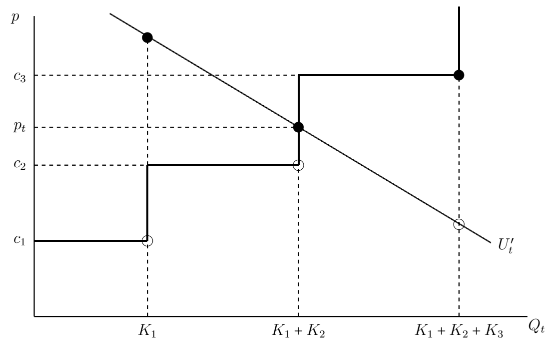
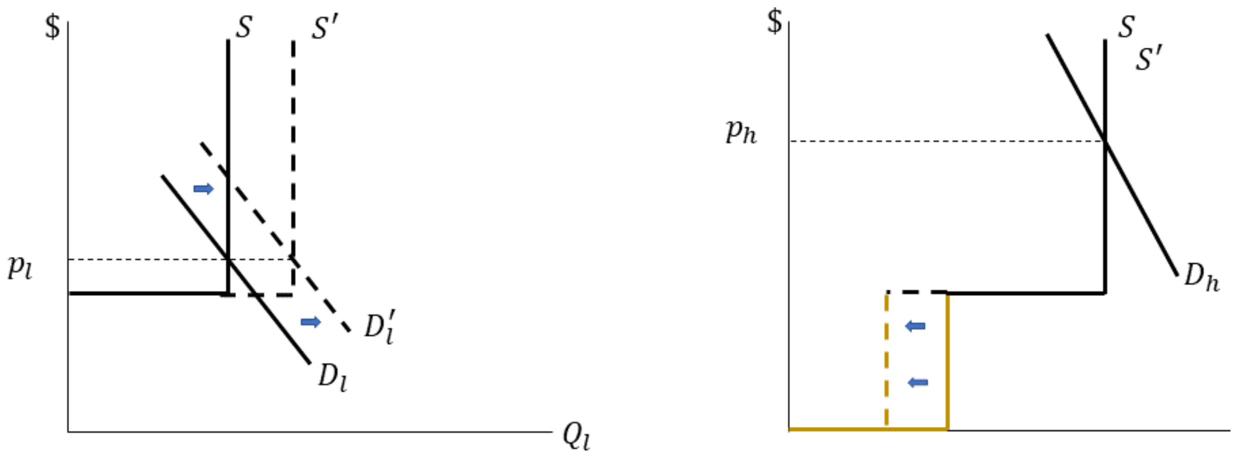


Figure O.A.1: Illustrative supply and demand with market clearing price p_t.

Notes: To illustrate Lemma 2, this figure assumes no storage and three technologies with capacity factors equal to one 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

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

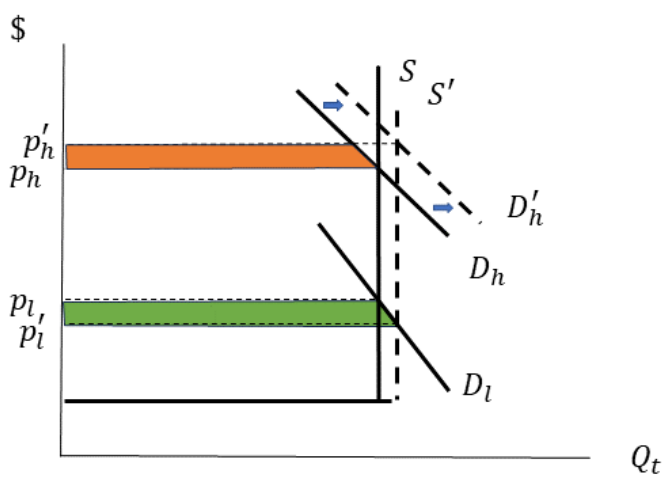
which is the minimum of three max expressions. The solid and unfilled circles indicate the values to be compared inside each of the max expressions, with the solid circles indicating the resulting maximum values. Thus $p_t = \min\{U_t'(K_1), U_t'(K_1 + K_2), c_3\}$, i.e., the minimum over the solid circles.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

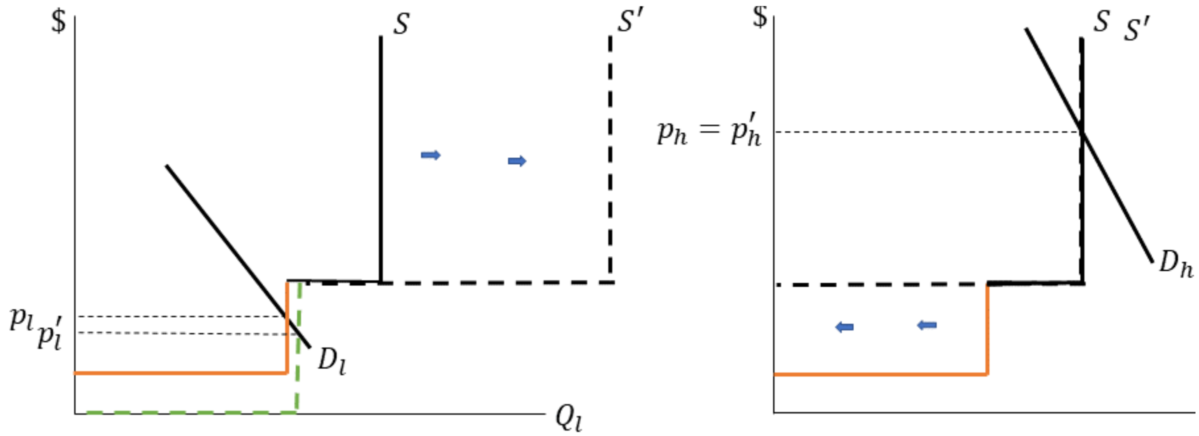
Notes: Two periods: h and l, and two technologies: intermittent renewable (1, yellow) and dispatchable fossil (2, black). Renewable produces only in period h. Equilibrium prices are given by $p_h = r_1$ and $p_l + p_h = 2c_2 + r_2$. Demand growth in period l increases gas capacity and decreases renewables,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



fig_Res_CS

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

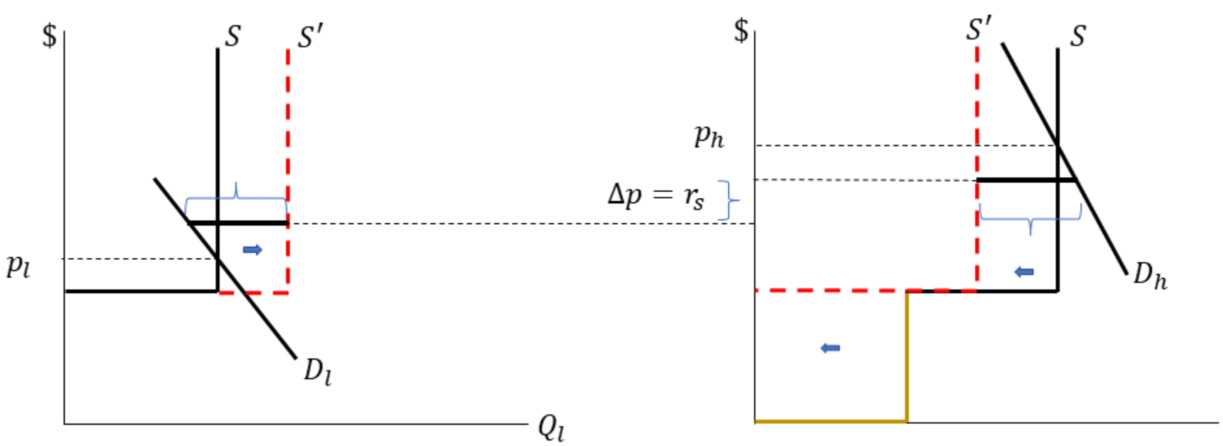
Notes: Two periods: h and l, and one technology with prices given by $p_l + p_h = 2c_1 + r_1$. Demand growth in period h increases p_h which decreases consumer surplus to the existing consumers by the orange trapezoid. Because $\Delta p_h = -\Delta p_l$, the existing consumers gain the green consumer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



_Res_renew

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

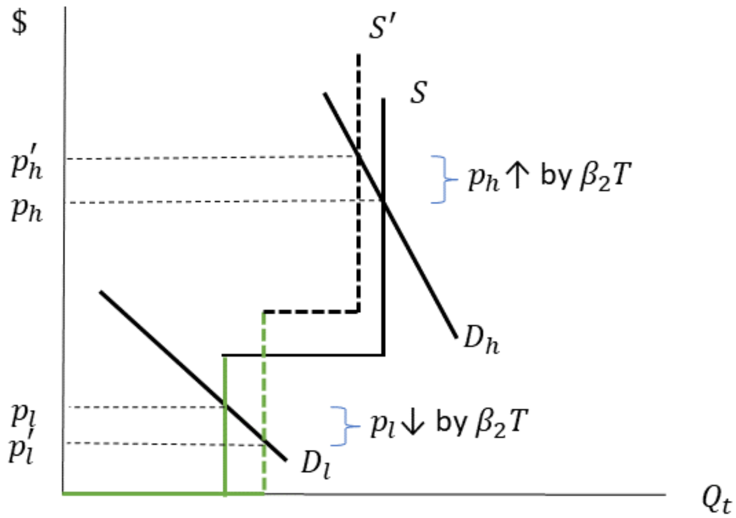
Notes: Two periods: h and l, and three technologies: intermittent renewable (1, green), nuclear (2, orange) and fossil (3, black). Renewable produces only in period l. High renewable cost has supply S from nuclear and fossil in both periods with prices $p_l + p_h = 2c_s + r_2$ and $p_h = c_3 + r_3$ and $p_l < r_1$. 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.



fig_Store

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

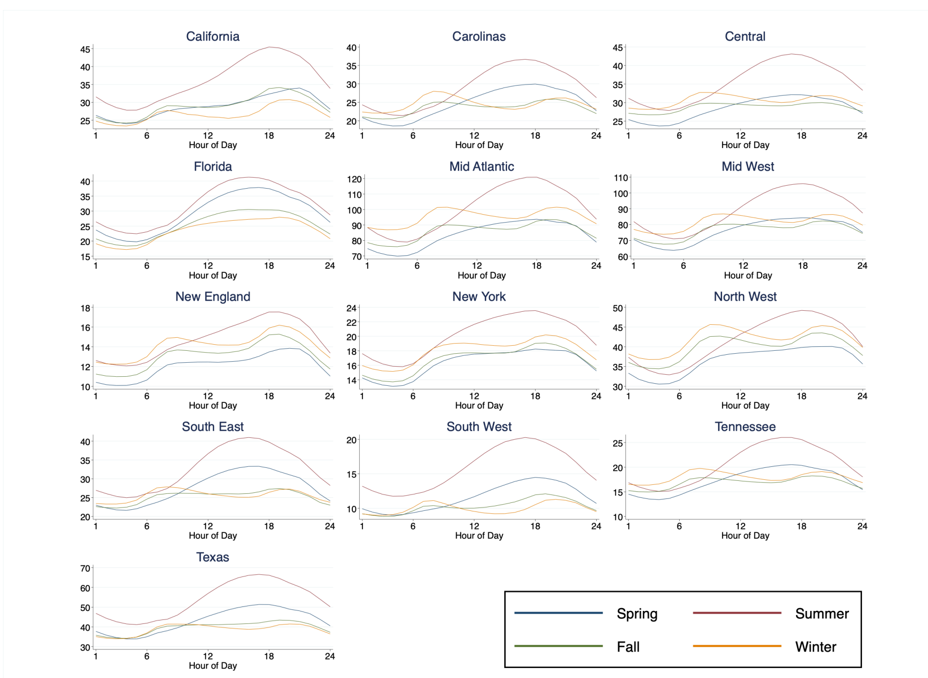
Notes: Two periods: h and l, and two technologies: intermittent renewable (1, yellow) and fossil (2, black). Renewable produces only in period h. Initially, r_s is large enough that there is no storage. The equilibrium has supply S and implies prices given by $p_h = r_1$ and $p_l + p_h = 2c_2 + r_2$. 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.



g_Res_Ctax

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

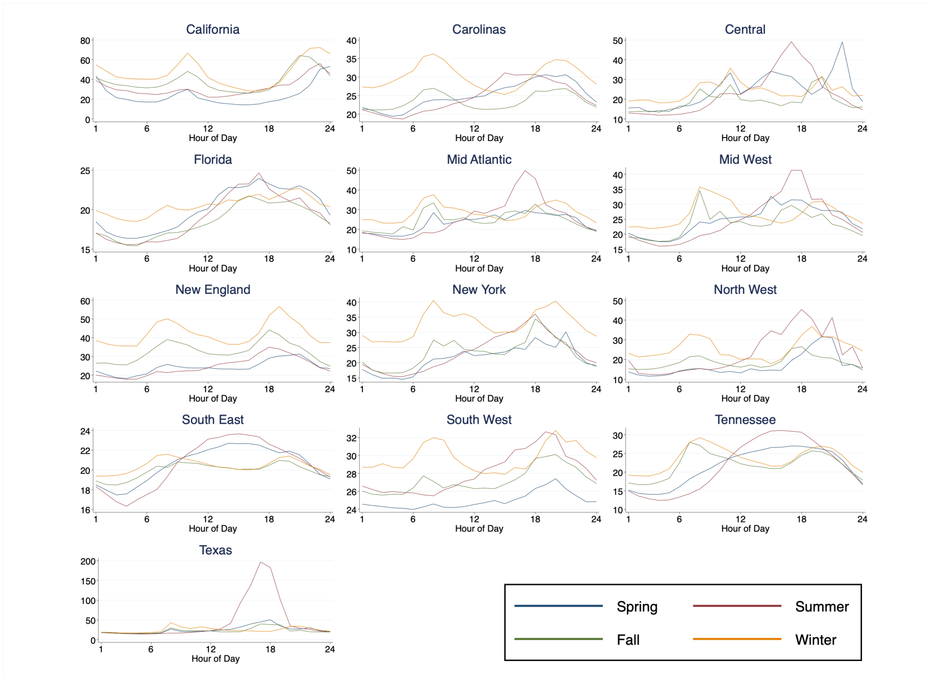
Notes: Two periods: h and l, and two technologies: renewable (1, green) and gas (2, black). Without carbon tax, supply is S, and prices are $p_l + p_h = r_1$ and $p_h = c_2 + r_2$. With a carbon tax T, supply is S', and prices are $p'_l + p'_h = r_1$ and $p'_h = c_2 + \beta_2 T + r_2$. Carbon tax increases 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.



efdemMulti

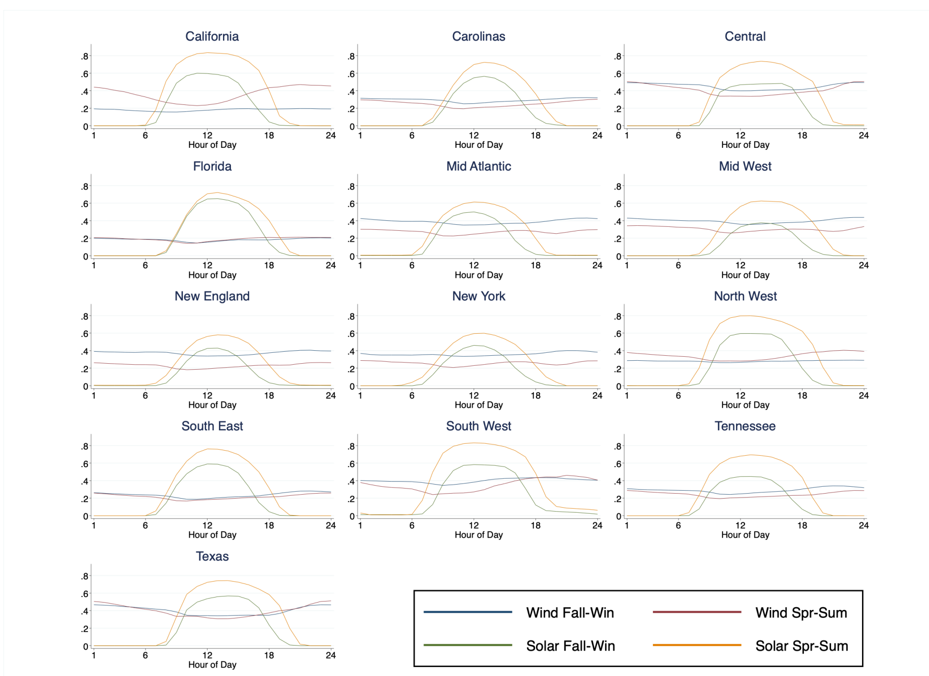
Figure O.A.7: Mean hourly observed demand by season and hour of day for each EIA region.

Notes: Demand in thousands of MWh.



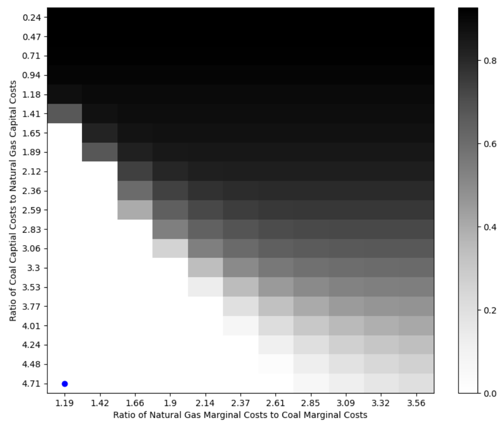
priceMulti

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



ig_cfMulti

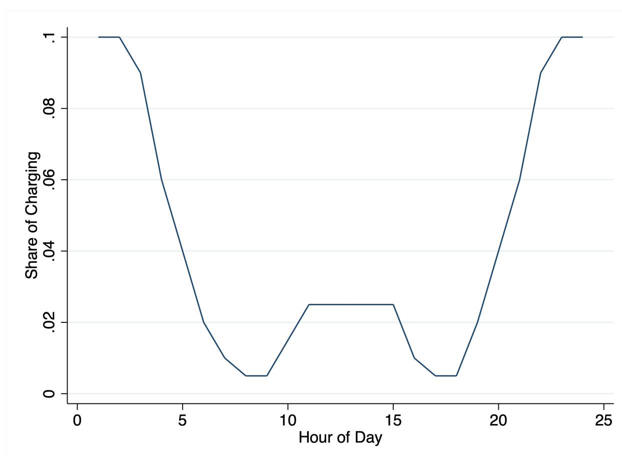
Figure O.A.9: Mean hourly capacity factors by season and hour of day for each EIA region.



_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.