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Timing Is Everything:

Optimal EV Charging To Maximize Welfare

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Abstract[1]

The new surge in electric vehicle (EV) charging in Texas can be served efficiently during the early morning hours with large wind generation, low electricity demand, low prices, and low environmental damage. This paper simulates the ERCOT wholesale electricity market and its environmental damages (CO_2, SO_2, NOx, and PM2.5) to find out how charging should be spread among hours to maximize welfare and the performance of different tariff schemes (hourly vs. day-night and private vs. social costs). The efficient charging schedule, incurring low costs and damages, is the opposite of current patterns: while users charge mostly in the evening (18-23 H), EVs should be charged during the first hours of the day (0-4 H). Constraining power withdrawals to the current Level 1 and 2 chargers reduces welfare gains since it limits using energy from those hours with lower prices and marginal damages. A day-night tariff reflecting social costs can achieve most of the gains of the first best, reducing carbon and air pollution damages below those of the current patterns.

JEL classifications: D62, L62, L94, Q41, Q53, Q54, R40
Keywords: EV charging, Wholesale electricity markets, Emissions taxes, Time-variant electricity pricing

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1. Introduction

Worldwide sales and new registrations of electric vehicles (EVs) have begun to increase exponentially. The United States, China and Europe are the leading developers and adopters of EVs, which will increase their electricity demand in the short and long run (IEA, 2017). In Texas, as this paper will discuss, the surge in power demand for charging EVs can be met efficiently during early morning hours of low electricity demand, large wind generation and a large unused generation potential of existing power plants. Furthermore, EVs are the key enabling technology for decarbonizing transportation and reducing air pollution in cities, as long as their power supply is clean.

Previous literature has modelled in detail the environmental impacts and economic benefits of EV charging in the United States, given current users' (non-optimal) charging patterns and in light of marginal increases (Holland et al., 2016; Graff Zivin, Kotchen and Mansur, 2014; Archsmith, Kendall and Rapson, 2015). In contrast, this paper assesses the charging schedule that maximizes welfare (private marginal generation cost and environmental damages) and two implementing tariff structures (hourly, day/night) for the estimated number of EVs in Texas. The results aim at informing policy and putting in place incentives (real time pricing, automated chargers) that can guide users to charge EVs during economically optimal hours.

I develop short-term partial equilibrium models of the wholesale electricity market in Texas (ERCOT) that replicate and calibrate the baseline (decentralized market problem with invariant tariff) and simulate how EV charging should be spread among hours to maximize welfare (First Best/Social Planner with hourly tariff) and surplus.[2] The models simulate via nonlinear optimization hourly electricity demand, fossil fuel generation, EV charging, prices, carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxide (NOx), and fine particulate matter (PM 2.5) emissions for Texas.

I estimate the fossil fuel supply curve using aggregate hourly fossil generation, heat input data, and monthly fuel costs for ERCOT generators in 2017 (EPA, 2019a; EIA, 2017). Furthermore, I use the exogenous variation of hourly load and wind to estimate wholesale hourly marginal emissions (CO_2, SO_2, NOx, and PM2.5) and air pollution damages (EPA, 2019a; ERCOT, 2017a). I use data on actual EV mileage by auto model in Texas, from the 2017 National

[2] The low level of imports makes ERCOT an ideal case for simulations.

Household Travel Survey (DOT, 2018), and owners' current non-optimal charging patterns from the EV Project in Houston and Dallas respectively (DOE, 2013b). The model also considers the hourly charging restrictions on the amount of energy that an EV can withdraw from the grid (Level 1 and 2 chargers). Finally, I simulate how day-night tariffs based on the socially optimal hours from the Social Planner's problem and charging generation costs and full social costs can implement second best solutions in a decentralized market.

The welfare-maximizing charging schedule is the opposite of current patterns: while users charge mostly in the evening (18-23 H) since they do not face an hourly price and due to convenience, EVs can be charged at the lowest marginal social cost during the first hours of the day (0-4 H). Unconstrained first best charging leads to welfare gains of up to 42 percent of wholesale prices over current non-optimal patterns: an average of 10.44 USD per MWh charged and lower carbon and air pollution damages than current charging patterns. Constraining power withdrawals to the current Level 1 and 2 chargers limits using energy from those hours with lower prices and marginal carbon emissions and reduces welfare gains. Nevertheless, even under the most restrictive L1, most EV charging can be done early in the morning, leading to welfare gains very similar to the first best (9.91 USD per MWh charged).

Even in the absence of emissions pricing on EV charging, the private surplus-maximizing charging schedule is similar to the welfare schedule due to the overlap of low prices and low marginal carbon emissions from hours 0 to 4. However, environmental damages increase at a much larger rate than prices from 5 to 8 AM, and the surplus maximizing schedule draws more power between those hours than the welfare schedule, leading to larger carbon emissions and air pollution than current charging patterns, and lower efficiency gains than the first best.

The second best day-night tariff charging only generation costs leads to an EV charging schedule that withdraws most power during 4-5 AM, and it captures up to 93.7 percent of the gains of the first best. However, this less granular period pricing reduces generation cost effectiveness and increases environmental damages compared to even the surplus-maximizing charging. On the other hand, the day-night tariff reflecting social costs leads to a charging profile that charges mostly from 3-4 AM, delivers more benefits (up to 98.3 percent of the gains of the first best) and reduces carbon emissions and air pollution damages below those of the current charging patterns. The day-night tariff is the "low-hanging fruit" since it can incentivize simple behavioral changes such as plugging in the EV not as soon as users get home but later on, allowing them to reduce their electricity bill and mitigate emissions damages. Aggregators who can bundle more than three users should be able to finance the initial cost of a smart charger and make a profit. I also show how the optimal schedule varies throughout seasons due to variation in demand and the marginal generator supplying power.

Under the current charging patterns of EV users, light-duty EV average CO_2 emissions per mile (176 g CO_2/mi) are less than half of those from the average passenger gasoline vehicle (404 g CO_2/mi) and average NOx emissions are 35.7 percent lower (DOE and EPA, 2019; Cai, Burnham and Wang, 2013). This occurs since most current charging takes place after the afternoon peak load (6-10 PM) when power is supplied by relatively clean combined cycle gas.

The conceptual and empirical model developed in this paper can be applied to grids mostly powered by fossil fuels (as is the case for several Latin America and the Caribbean and developing countries worldwide) to find the schedules with the lowest private generation cost and environmental damages.

The paper is organized as follows. Section 2 discusses the economic literature on assessing the impacts of electric vehicles. Section 3 presents the main market, prices and wind power trends in ERCOT. Section 4 starts with an overview of the numerical models for the Social Planner and decentralized simulations of the wholesale market, then describes the demand, marginal cost, emissions and damages functions estimation and calibration as well as the charging restriction parameters. This section closes with a detailed presentation of the algorithms for simulating the models. Section 5 presents the results of the optimal charging schedules, including their welfare and emissions impacts for the different tariff schemes. Finally, Section 6 presents discusses the results and policy implications, and Section 7 concludes.

2. Literature Review

Different authors in the economic literature have argued that the benefits of using EVs depend on the location and timing of their charge. Graff Zivin et al. (2014) show that different marginal power plants serve a shifting load during the day, which in turn determines heterogenous carbon, sulfur and nitrogen oxide emissions. Hence, the environmental impact of an electric vehicle will depend on the charging schedule. The authors find that the average carbon emissions per mile of an EV in Texas (> 195 gCO_2/mi) are lower than those from a hybrid car independently of its charging hours. However, for other regions of the United States, an EV can have lower carbon emissions than a hybrid only if charged during specific hours (for example, from 9PM-12AM in the Northeast Power Coordinating Council and from 9-12AM in the Southwest Power Pool).

Archsmith, Kendall and Rapson (2015) estimate the abatement potential of switching from an internal combustion engine car to an EV by modelling its life cycle carbon emissions. The authors find that EVs slightly reduce carbon emissions on average but with large regional variations across the United States. The operation or driving emissions of EVs are based on the engineering GREETnet model, which renders average emissions factors for power generation. While this study undertakes a detailed analysis of total EV lifecycle emissions, it uses two charging schedules (day and night) and does not explore what an optimal schedule would look like.

Holland et al. (2016) assess the environmental benefits of electric vehicles compared to their gasoline counterparts using a comprehensive modelling of the choice of vehicle purchase, the carbon, sulfur and nitrogen oxide marginal emissions from charging and the related spatial damages. The authors compare the environmental benefits of EVs to those of gasoline vehicles to shed light on how to target adoption subsidies. EVs benefits and subsidies depend on where they are charged: the Western states and some Texas counties obtain significant benefits due to their clean power grid, while the rest of the country does not. The authors analyze a charging profile based on results of the Electric Power Research Institute, a flat profile and six others combining four-hour charging blocks. Those profiles do not necessarily reflect the optimal charging hours that would minimize the generation cost and maximize welfare gains from charging EVs.

Ensslen et al. (2018) model and analyze the market impacts of a load-shifting tariff for EV charging in France and Germany. The authors perform detailed simulations of how different tariff schemes affect the business model and the profitability of charging managers or aggregators. Profitable charging by aggregators shifts EV load from the afternoon and evening to night and from the morning to noon in both countries. This occurs since prices at night and noon are lower in both areas due to lower demand and the contribution of renewables. The authors model neither the environmental impacts of shifting EV load nor strategies for maximizing welfare beyond aggregators' profit.

A recent experiment by Burkhardt, Gillingham and Kopalle (2019) shows how off-peak pricing can provide EV users with the appropriate signals to charge vehicles at the lowest cost. By reducing prices from 9 to 2 cents per kWh between 10 PM to 6 AM for treatment households selected at random in Austin, the authors find a large increase in electricity consumption from

2AM–5AM, with electric vehicles being the main load shifted. This off-peak pricing schedule reflects the variation in marginal generation cost and incentivizes adopting the optimal charging schedule. Ideally, this schedule should vary at least seasonally to reflect different marginal generation costs and emissions for different load levels throughout the year.

A previous project by the Department of Energy also found that EV users respond to time-of-use rates in deciding when to charge. Given an off-peak pricing schedule, with lower prices from midnight to early morning hours than those during the rest of the day, users responded to the incentives by starting EV charging around the initial hour of off-peak pricing (DOE, 2013a).

To the best of my knowledge, the novel contributions of my research are the following. The first is to simulate how household EV charging should be spread among hours to maximize welfare (Social Planner problem with hourly prices reflecting social marginal costs) and surplus (hourly prices reflecting only private marginal costs). Second, I assess the optimal charging schedules by using a detailed model of charging restrictions, hourly private generation costs and marginal damages from carbon, sulfur, nitrogen oxide and PM2.5 emissions. Finally, I show how day-night tariffs, based on the optimal hours from the Social Planner problem, can implement second best solutions in a decentralized market.

3. Electricity Market Prices, Marginal Emissions and EVs in Texas

The best EV charging schedule is one that charges the vehicle at a time that minimizes generation cost and environmental damage. Hence, the optimal charging hours will be those with the lowest electricity prices and marginal damages. Any misalignments between those two factors will create tradeoffs between generation cost effectiveness and full efficiency, which internalizes EV charging damages.

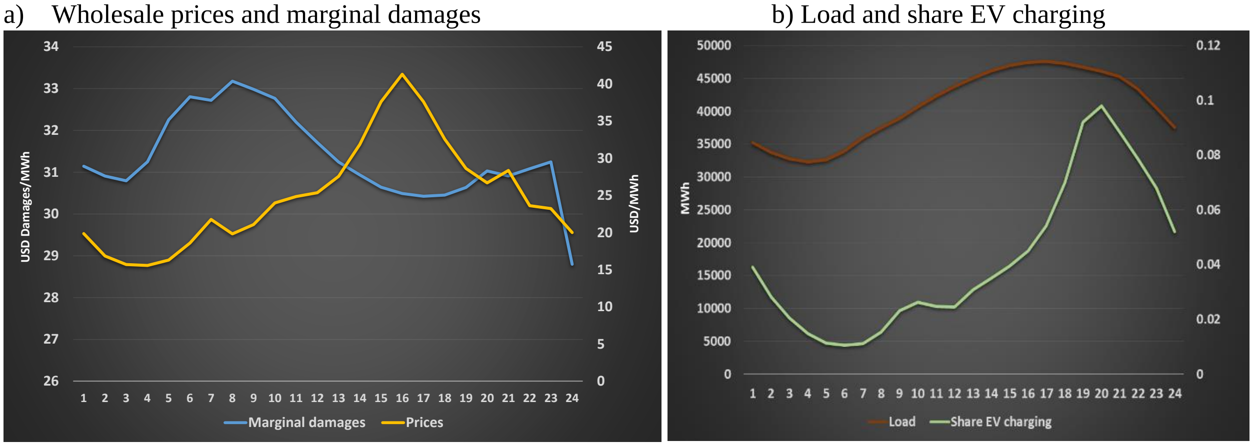
In ERCOT, the lowest generation prices occur late at night and early in the morning (23-24, 1-6 H) since power demand is low during those hours and is met with low-cost generation coming mostly from steam coal turbines, combined cycle natural gas and wind. The lowest marginal damages from CO_2, SO_2, NOx and PM2.5 emissions also coincide with those hours. However, as the workday starts and load increases from 7 to 8 AM, there is a morning peak in prices and a much steeper increase/peak in marginal damages, which lasts for a couple of hours (Figure 1).

Throughout the morning and afternoon load increases, and it is met with more costly marginal natural gas generation, driving electricity prices up but reducing marginal damages due to the cleaner fuel. Hence, there is a tradeoff between reduced environmental damages and higher cost when charging EVs during those hours (for example, while parking at work). By the end of the day, as the lights turn off, load decreases and so do prices while marginal damages remain almost the same. These prices and marginal damages patterns determine what the optimal EV charging schedules should be when users account for only electricity prices or for full marginal social costs. Certainly, any optimal schedule will withdraw most power during the very first hours of the day.

Figure 1. Average Wholesale Electricity Prices, Load, Marginal Damages and EV Charging

a) Wholesale prices and marginal damages

b) Load and share EV charging



Source: ERCOT, 2017c. Marginal damages are based on regression estimates described in the sections below.

On the other hand, current household EV charging patterns in Houston and Dallas exhibit the opposite shape of an optimal schedule. Most power is withdrawn during the evening peak between 7-9 PM after owners return to their homes; this leads to excessive generation cost and environmental damages (DOE, 2013a). These patterns occur since most users face the same electricity tariff during all hours and have no incentives and signals to charge their EV at the optimal time.

While the market share of electric vehicles in the United States was 0.91 percent and 1.18 percent in 2016 and 2017, respectively, EV adoption has an exponential trend (IEA, 2017). Texas has a market share slightly lower than the national rate, but it nearly tripled from 0.39 percent to

0.95 percent between 2017 and August 2018 (EV Adoption, 2019). This growing charging demand will create inefficiencies and challenges if all charging takes place during peak hours.

4. Empirical Model

4.1 Overview

I develop short-term, partial equilibrium models of the wholesale electricity market in Texas (ERCOT) whose goals are: i) to replicate and calibrate the baseline (decentralized market problem with invariant tariff); ii) to simulate how household EV charging should be spread among hours to maximize welfare (Social Planner problem with hourly prices reflecting social marginal costs) and surplus (hourly prices reflecting private marginal costs); and iii) to model how day-night tariffs based on the optimal hours from the welfare maximization problem and charging private generation and social costs can implement second best solutions in the decentralized market.

The Social Planner problem simulates either welfare or private surplus maximization by choosing fossil generation and EV charging. It assumes a one-day horizon with hourly time steps *t*, and no discount. Electricity demand $P_t(q_t)$ is represented with a linear functional form, private generation costs $C(f_t)$ are captured with an exponential function, wind power w_t is based on historical output, EV_t stands for light duty plug-in hybrid (gasoline) electric vehicles and electric vehicles charging demand and *nuke* is a constant capturing the average hourly base nuclear generation of 4,395.45 MWh in 2017.

$$(1)\ Max_{\boldsymbol{f},\boldsymbol{EV}} \sum_{t=0}^{23} \left[\int_0^{q_t} P_t(q_t) dq_t - C(f_t) \right]$$

$$s.t. \sum_{t=0}^{23} EV_t = \overline{EV}$$

$$q_t + EV_t = w_t + f_t + nuke_t$$

$$\textit{and charging constraints}$$

I model the short-term impacts of light-duty EV charging on wholesale generation market welfare, surplus, CO_2, NOx, SO_2 and PM2.5 emissions. For this, I assume that total charging demand is determined separately and exogenously by users when deciding what EV to purchase and how much to drive. This conjecture is sensible since users do not value the amount of power for charging itself but rather the miles that they can drive with it. Thus, the Planner aims to allocate hourly charging demands to have the smallest impact on power generation welfare and surplus.

While the objective in equation (1) represents the market surplus, I model welfare maximization by considering the marginal damages of EV charging. Since the response of generators to a carbon price would be low in the short run, a \$20 (\$70) per ton increase reducing emissions by 5 percent (10 percent) according to Cullen and Mansur (2017) and Cullen (2016), I focus only on the damages caused by meeting new EV charging demand. Hence, the modelling would be analogous to implementing emissions taxes only on EV charging.

For modelling the baseline and day/night tariff scenarios in a decentralized market I use the following equilibrium conditions:

2) $P_t(q_t) = p_d \; \forall t$
3) $C'(f_t) = {p_t}^w \; \forall t$
4) $q_t + EV_t = w_t + f_t + nuke_t$
5) ${p_d}^r \sum_{t=0}^{23}(q_t + EV_t) = \sum_{t=0}^{23}[(w_t + f_t + nuke_t) * {p_t}^w]$
6) charging constraints

Equation (2) represents the consumer optimality condition, which equates all hourly marginal benefits to one daily tariff p_d. The producer optimality condition in equation (3) states that hourly marginal costs are equal to hourly wholesale prices ${p_t}^w$. Finally, the cost recovery condition in equation (5) sets forth that the income charged to consumers for power consumption, including EV charging, must equal total payments to all generators. For day-night tariffs, the consumer and the cost recovery condition change to reflect two daily tariffs.

The models described above represent surplus and welfare at the wholesale generation level, and they do not capture fixed costs, distribution tariffs and losses. In this paper I choose to focus on EV charging impacts on generation and emissions, and modelling welfare and surplus at the wholesale level does a good job of capturing the main features and insights of power generation.[3] I do not address the access to charging facilities problem, since the models aim at finding the best charging hours from a wholesale generation standpoint. It is worth noting that the models estimate upper bounds on welfare since they assume a static approach to ramp-up and

[3] I discuss this further and show detailed results graphs in the baseline calibration results.

startup constraints, and no transmission congestion costs. Furthermore, they do not consider long-term investments in fossil and nuclear capacity.

4.2 Demand and Fossil Generation Cost Calibration

Average electricity demand and generation costs are parameterized with publicly available information on hourly load, generation, fuel use, and prices for 2017 from the U.S. EIA 923 Form, the EPA's continuous emissions monitoring system (CEMs) and ERCOT (EPA, 2019a; ERCOT, 2017a; ERCOT 2017c; EIA, 2017). Demand is calibrated with a linear functional form $(P_t = a_t - b_t * (q_t))$ and an elasticity of -0.09, which is a sensible estimate for the hourly pricing and short-run elasticity of power demand (Deryugina, MacKay and Reif, 2020; Wolak, 2011). I compute the demand parameters for each hour *t* of each day *d* of 2017 using load and average monthly wholesale prices, since most end-users face monthly tariffs, to solve the two-linear-equation system comprised of the demand function and the elasticity equation $\left(\varepsilon = \frac{\delta Q_t P_t}{\delta P_t Q_t}\right)$. Hence, there are 8,760 different intercepts a_{td} and slopes b_{td} for the simulations.

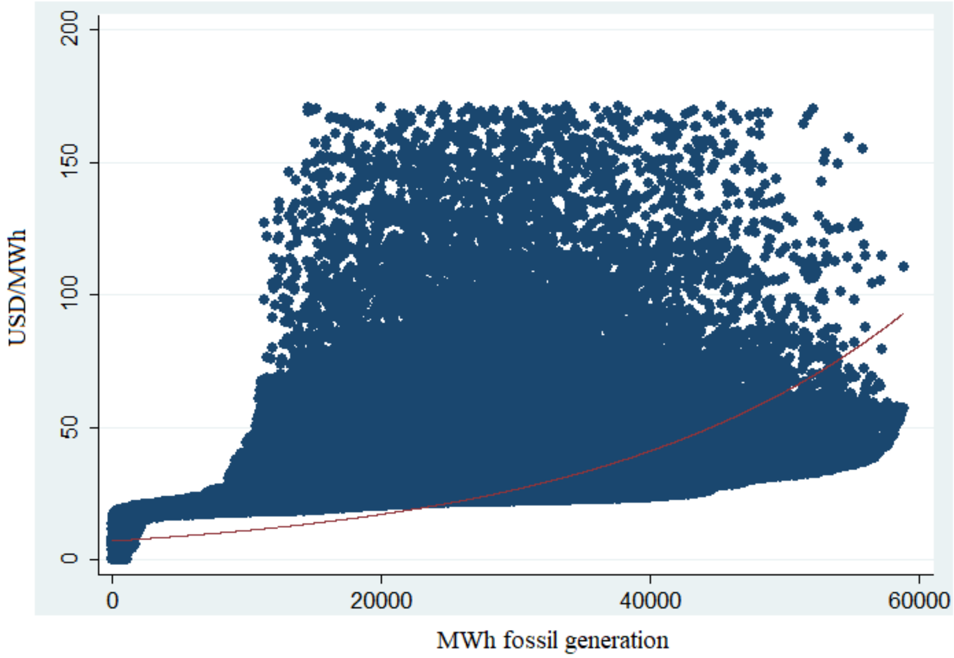
Using hourly fossil generation, heat input data, and monthly fuel costs for all generators, I build the hourly fossil marginal generation cost (MC) of the wholesale market electricity dispatch (EIA, 2017; EPA, 2019b). The approach consists of computing hourly heat rates (mmBTU/MWh) for all coal and gas generators in ERCOT during 2017 using the EPA Air Markets Program Data (AMPD).[4] Then, I compute hourly generation costs of each generator by multiplying this heat rate by its monthly average fuel cost using the 2017 EIA Form 923.

I order the plants and their dispatches using the generation cost, in a merit order way, to obtain 8,760 hourly wholesale marginal cost curves. Then, I obtain the average wholesale fossil marginal cost curve $C(f_t)$ by fitting an exponential functional form ($R^2 = 0.7$), which is the most parsimonious form and captures the inelasticity of supply at peak demand (Figure 2).[5] This idea is similar to the approach used by Reguant (2018) for approximating the marginal generation cost, but the author used year-average heat rates and a piece-wise function instead.

[4] I select those generators which are in ERCOT by matching the generators in Texas from the AMPD database to their respective balancing authority identified in EIA Form 923 using the ORISPL code. The previous matching also makes it possible to classify the generators by fuel type.

[5] Before fitting the exponential functional form, I eliminated extreme outliers, which represented 0.1 percent of all the data.

Figure 2. Private Fossil Generation Marginal Costs in ERCOT



Source: Author's compilation based on EPA (2019a) and EIA (2017).

The model and the marginal cost calibration incorporate fuel costs related to startups and ramp-up constraints through the total amount of fuel used for power generation and reported in the CEMS database for all hours of 2017. Hence, this approach is a static version of the actual dynamic problem of power generation with start-up costs and ramping constraints since the amount of fuel used to deal with those frictions is reflected in the hourly heat rates computed for each generator (Cullen and Reynolds, 2016).

4.3 Marginal Damages and Emissions

In order to analyze the environmental impacts of the different EV charging schedules, I obtain the hourly marginal damages and emissions from an increase in demand by regressing the wholesale aggregate hourly air pollution damages and CO_2, SO_2, NOx, and PM2.5 emissions on the exogenous hourly variation in wind power and load in ERCOT in 2017 (EPA, 2019b; ERCOT, 2017a, 2017b). I use the aggregate wholesale hourly CO_2, SO_2, and NOx emissions from EPA's Air Markets Program Data (EPA, 2019a).

I compute the hourly PM2.5 emissions following Fell, Kaffine and Novan (2019) to i) obtain emissions rates (lbs/MWh) by dividing county level coal and gas power plants PM2.5

emissions from the 2014 National emissions inventory (EPA, 2019b) by annual power generation from EIA Form 923 and ii) impute those rates to all hourly coal and gas generation in ERCOT as reported in EPA (2019a). I use the central estimate for a 3 percent discount rate of the social cost of carbon (42.02 USD/t CO_2 in 2017 dollars), which is the conventional estimate used in the literature (IAWG, 2015; Cullen, 2013; Novan, 2015).

I compute hourly aggregate wholesale level air pollution damages by using county-level air pollution marginal damages for SO_2, NOx, and PM2.5 medium and tall stacks emissions from the AP2 Model used in Holland et al. (2016). The marginal damages include morbidity and mortality and use the EPA's recommended value of a statistical life. I match these county-specific marginal damages with the location of the power plants stated in Form EIA-860 and sum all air pollution damages for each hour in ERCOT. I calculate and report all damages in 2017 dollars.

To estimate marginal emissions and damages, I use a linear polynomial with hourly interactions specification as in Graff Zivin et al. (2014) and control for weekly and weekend fixed effects (equation (7)). I estimate the standard errors using Newey-West with 24-hour and 168-hour lags.

$$(7)\ Y_t^m = \beta_{0m} + \sum_{h=0}^{23} \beta_{lhm}\, HOUR_h * D_t + \sum_{h=0}^{23} \beta_{whm}\, HOUR_h * W_t + \delta_w + \gamma_{we} + \varepsilon_t$$

where:

Y_t^m represents m different emissions (tCO_2, lbs SO_2, lbs NOx, and lbs PM2.5) and total air pollution damages (summation of SO_2, NOx, and PM2.5 damages in 2017 USD) at hour t,

W_t, D_t are ERCOT aggregate wind power and demand (load) in MWh at hour t,

δ_w stands for weekly fixed effects and γ_{we} for weekend FE,

$\boldsymbol{\beta}$ are regression coefficients.

The average partial effects $\widehat{\beta_{lhm}}$ give the estimate of the hourly marginal emissions and damages of increasing load in one MWh, which I use to compute the emissions and welfare impact of increasing load to charge EVs. Estimation results are in Appendix 3.

4.4 EV Charging Demand

I use data on the number (N_s) of plug-in hybrid (gasoline) electric vehicles and full electric vehicles and their actual mileage by auto model (s) in Texas, from the 2017 National Household

Travel Survey NHTS (DOT, 2018).[6] I compute daily individual charging demand for all models of plug-in hybrid and fully electric vehicles ($\overline{ev_s}$) assuming the same daily use for the total annual miles estimated in the NHTS and using the fuel economy (kWh/mi) reported by the U.S. official source (DOE and EPA, 2019).

I use battery size and charging time parameters to model the hourly charging restrictions and the amount of energy (MWh) that an individual EV can withdraw in an hour for each vehicle type s. As charging restrictions vary according to the type of charger used, I consider the L1 and L2 commercially available types, where the latter allows withdrawing more energy in a given hour and faster charging (ClipperCreek, 2019).[7]

Using the above described parameters, the charging constraints of the maximization problem are:

$$(8) \sum_{s}\sum_{t=0}^{23} N_s * ev_{st} = \sum_{s}(N_s * \overline{ev_s}) = \sum_{t=0}^{23} EV_t = \overline{EV}$$

$$(9)\ ev_{st} \leq \frac{battery\ size_s}{L\ charging\ time_s} \quad \forall s$$

Equation (8) states that the summation of hourly individual charging demands ev_{st} should equal the total daily charging demand of all EVs ($\overline{EV}$), and equation (9) states that no single vehicle can withdraw more energy (MWh) than what its hourly charging restriction allows. For the optimization scenarios whose goal is to simulate how EV charging should be spread among hours ev_{st} is a decision variable to be optimized. For the scenarios simulating owners' current non-optimal charging patterns ev_{st} is a parameter based on the hourly patterns and shares from the EV Project data in Houston and Dallas (DOE, 2013b).

[6] The survey identifies 23 vehicle models, including those catalogued as others. For details on the parameters see Appendix 1.

[7] I use the slowest charging technologies of each type, Level 1 ACS 15 1.4 kW and Level 2 LCS 20 3.8 kW, to obtain conservative estimates of the optimal EV charging schedule in the constrained scenarios. Level 1 is equivalent to plugging into the common household outlet (110 V), while level 2 has a higher voltage (220 V).

4.5 Policy Scenarios and Simulations

I compute results for fossil generation, EV charging, surplus, welfare and emissions (CO_2, NOx, SO_2 and PM2.5) using simulations based on the 2017 data for 14 scenarios:

<table>
<tr><td></td><td colspan="6">Tariff</td></tr>
<tr><td rowspan="4">Charging Constraints</td><td>Welfare maximizing</td><td>Surplus maximizing</td><td>Day-night tariff</td><td>Day-night social costs tariff</td><td colspan="2">Day invariant tariff</td></tr>
<tr><td>Unconstrained</td><td>Unconstrained</td><td>Unconstrained</td><td>Unconstrained</td><td rowspan="3">Current charging patterns</td><td rowspan="3">Baseline no EV charging</td></tr>
<tr><td>L2</td><td>L2</td><td>L2</td><td>L2</td></tr>
<tr><td>L1</td><td>L1</td><td>L1</td><td>L1</td></tr>
</table>

The day-night tariff scenarios have the same structure, with two daily prices to consumers, except that one charges only generation costs and the other charges social costs, which include generation and environmental damages. There is only one current patterns scenario since the charging schedule and amounts are based on the hourly shares from the EV Project Data, which comply with the L1 and L2 charging technologies (the default available options). Finally, the baseline scenario reproduces the results of the decentralized 2017 market without modelling any EV charging.

The algorithm consists of the following steps:

1. Draw 24-hour-wind power profiles (w_{it}), demand parameters (a_{it}, b_{it}), and other generation profiles (ot_{it}) from all 365 days of 2017.[8]
2. For the welfare and surplus optimization problems, solve the below maximization problem with the Non-Linear Programming Solver (NLP) from GAMs and find the optimal fossil generation and EV charging for each hour (t) of the i^{th} draw.

[8] Other generation includes hydro, biomass, solar and imports/exports. It represents less than 1 percent of all power generation and is modelled as fixed baseline power since its low share does not significantly affect the results.

$$(10)\ Max_{\boldsymbol{f,EV}} \left[\begin{array}{c} \underbrace{\sum_{t=0}^{23} \int_0^{f_{it}+w_{it}+nuke+ot_{it}-\sum_s \sum_{t=0}^{23} N_s * ev_{ist}} [a_t - b_t q_{it}] dq_{it}}_{Benefits} \\ \underbrace{-\sum_{t=0}^{23} d * e^{gf_{it}}}_{Fossil\ generation\ cost} \underbrace{- \sum_{t=0}^{23} g * d * e^{gf_{it}} * (w_{it} + nuke + ot_{it})}_{Payments\ nuclear\ and\ wind\ power} \\ -\sum_{t=0}^{23} \underbrace{\left(\sum_s N_s * ev_{ist} \right)}_{Electric\ vehicle\ charge} \left(\underbrace{\tau^{CO_2} * \widehat{\beta_{lt\,CO_2}}}_{Carbon\ marginal\ damages} + \underbrace{\widehat{\beta_{lt\ air\ poll}}}_{Air\ pollution\ marginal\ damages} \right) \end{array} \right]$$

$$st: \sum_s \sum_{t=0}^{23} N_s * ev_{ist} = \sum_s (N_s * \overline{ev_s})$$

$$ev_{ist} \leq \frac{battery\ size_s}{L\ charging\ time_s} \quad \forall s$$

In the surplus maximization scenario, the objective function in equation (10) drops the third line, which represents the environmental damages from EV charging. Nevertheless, when I assess and compare the welfare from charging EVs based only on private marginal costs, I compute net welfare by subtracting environmental damages from the optimized surplus.

For the decentralized market problems (current patterns, day-night tariff and baseline), I solve the below system of equations using the Non-Linear Programming Solver (NLP) from GAMs and find hourly fossil generation, EV charging, wholesale generation prices and the daily tariff for each i^{th} draw.

$$11)\ \underbrace{P_t\left(f_{it} + w_{it} + nuke + ot_{it} - \sum_{s}\sum_{t=0}^{23} N_s * ev_{ist}\right)}_{\textit{Marginal benefits}} = p_d\ \forall t$$

$$12)\ \underbrace{\sum_{t=0}^{23} g * d * e^{gf_{it}} = p_t{}^{w}\ \forall t}_{\textit{Marginal fossil generation costs}}$$

$$13)\ \underbrace{p_d{}^{r} \sum_{t=0}^{23}\left(f_{it} + w_{it} + nuke + ot_{it} + \sum_{s}\sum_{t=0}^{23} N_s * ev_{ist}\right)}_{\textit{Total payments by consumers}}$$

$$\underbrace{= \sum_{t=0}^{23}[(f_{it} + w_{it} + nuke + ot_{it}) * p_t{}^{w}]}_{\textit{Total payments to generators}}$$

In the baseline scenario, the EV charging terms are dropped from the above system of equations. For the current patterns scenario, EV charging terms are given parameters and no longer variables to solve for. For the day-night tariff scenarios, the consumer total payments and optimality conditions change to reflect two tariffs instead of one. For all the decentralized market models, the charging restriction equations also become a part of the system.

Since the above system of equations is highly non-linear it has several possible roots. To find the best possible root that calibrates the baseline and then from there simulates the counterfactual tariffs, I maximize surplus in the case of the baseline and the private costs day-night tariff subject to equations (8-9) and (11-13) as restrictions. For the social costs day-night tariff scenario, I maximize welfare subject to the restrictions of equations (8-9) and (11-13). Maximizing welfare permits representing how users would respond to a tax on marginal environmental damages (carbon and air pollution).

Finally, I compute welfare for the decentralized market scenarios using the objective function in equation (10) evaluated at the fossil generation and EV charging levels solved in the decentralized models.

3. Compute the average and 95 percent confidence intervals of hourly fossil generation (f_{it}), EV charging ($EV_{it} = \sum_s N_s * ev_{ist}$), emissions ($E^m{}_{it} = \sum_s \sum_{t=0}^{23} N_s * ev_{ist} * \widehat{\beta_{ltm}}$), and welfare ($W_i$) for all 11 scenarios.
4. Compute the welfare gains of the optimized EV charging scenarios with respect to the current patterns scenario by subtracting total gains from the dispatch optimization gains:

$$Gains\ EV\ charging_i = \underbrace{\left[W_i^{Opt\ scenario}\left(\boldsymbol{EV_i^*}\right) - W_i^{current\ \ patterns}\left(\boldsymbol{EV_i^{curr.pat}}\right)\right]}_{\text{Total Gains}}$$

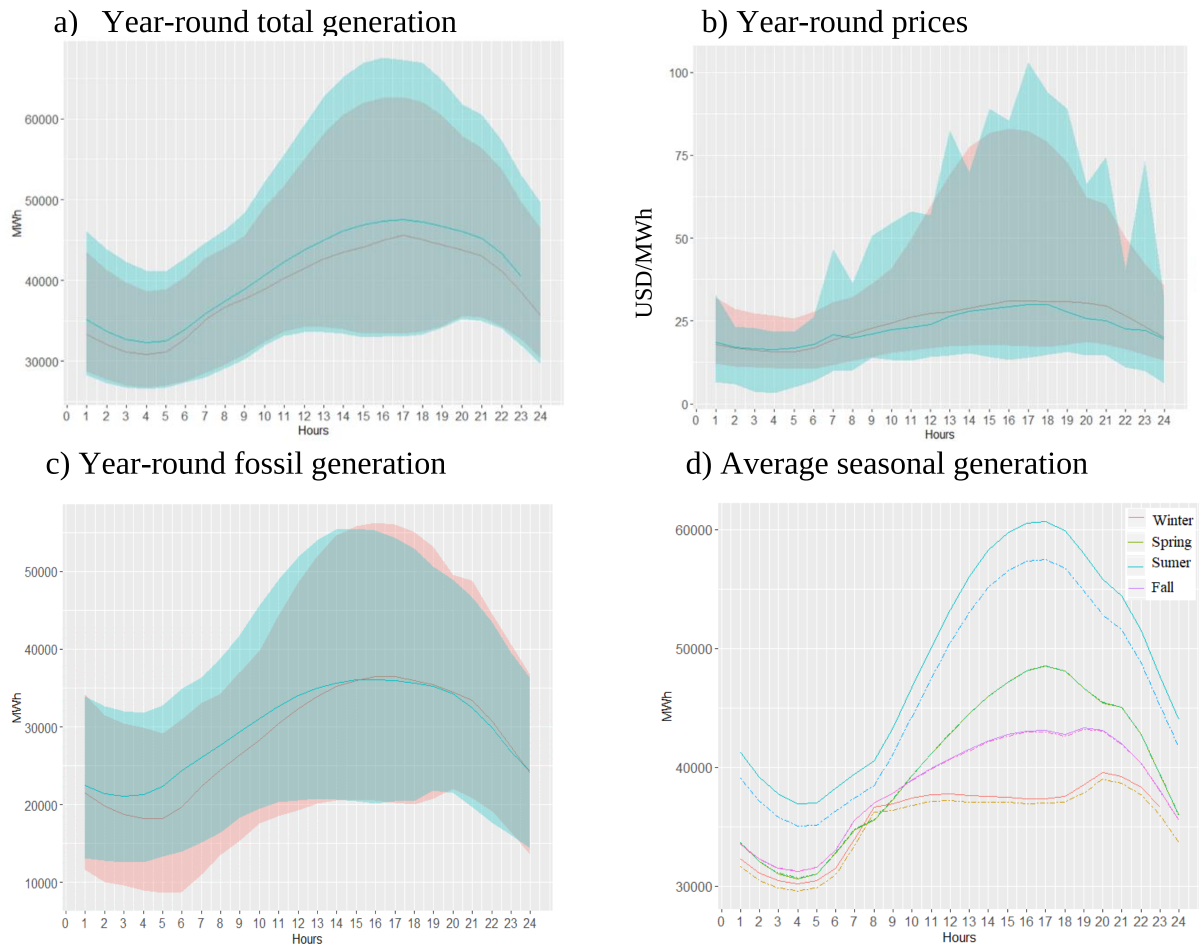
$$-\underbrace{\left[W_i^{Opt\ scenario}\left(\boldsymbol{EV_i^{curr.pat}}\right) - W_i^{current\ \ patterns}\left(\boldsymbol{EV_i^{curr.pat}}\right)\right]}_{\text{Gains from dispatch optimization}}$$

5. Results

5.1 Baseline Calibration

I assess the adequacy of the assumptions, functional forms and methodology for reproducing ERCOT’s wholesale generation market by comparing the values and trends in the simulated median and 95 percent confidence intervals of prices and generation to those of the historical data in 2017. The baseline calibration reproduces fairly well the median and trends for the entire year and even for different seasons (Figure 3). By relying on a static version of the startup and ramp-up costs, with no transmission congestion constraints, the proposed approach captures with simplicity the main features and results of wholesale electricity markets and their environmental impacts.

Figure 3. Baseline Calibrations Results



Notes: Blue are historical data, and red are simulated data. The band depicts a 95 percent confidence interval, while the solid lines represent medians.

5.2 Charging Schedules

The welfare-maximizing EV charging schedules are the opposite of current non-optimal patterns: while users charge in the evening since they do not face an hourly price and due to convenience, EVs can be charged optimally at home during the first hours of the day at the lowest marginal social cost. For all charging technologies, the bulk of optimal power withdrawals should occur very early in the morning (3-4) and by the end of the day (23-24), as shown in Figure 4a. Constraining power extractions to slower chargers displaces withdrawals to 2 and 5 AM. The current charging patterns based on the EV project trends comply with both L1 and L2 charging restrictions, which reflects that under the available technologies, users spread their demands through the day. Nevertheless, most current charging occurs during the evening peak (19-21) leading to excessive generation cost and environmental damages (Figure 4a).

Even in the absence of emissions pricing on EV charging, the private surplus maximizing charging schedules are similar to the welfare schedules due to the overlap of low prices and low marginal damages from hours 0 to 4. Since damages increase at a much greater rate than prices from 5 to 8 AM, but the surplus maximizing schedule does not consider full social costs, it draws more power between those hours than the welfare-optimizing schedule (Figure 4b).

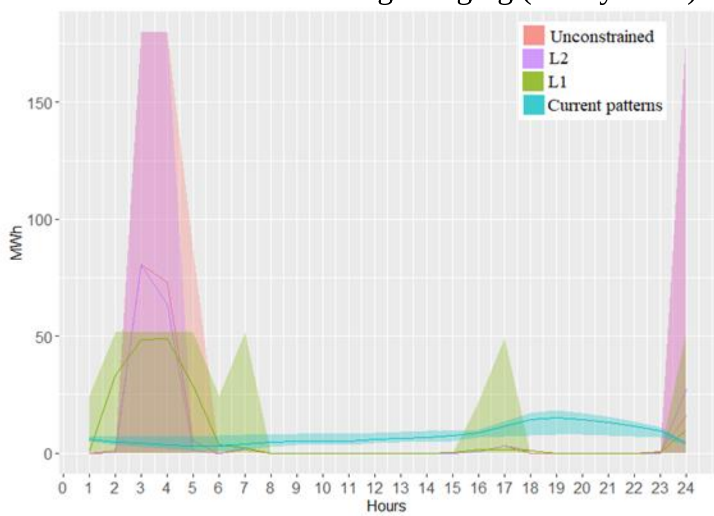
The second-best day-night tariff, charging only private generation costs but based on the optimal hours from the welfare maximization problem (1-7, 24), leads to an EV charging schedule that withdraws most power during 4-5 AM (Figure 4c). The simulation results presented here are in line with real world randomized experimental results of the day-night tariff in Austin, which show that households that received the day-night tariff treatment charged their EVs mostly at 4 AM (Burkhardt, Gillingham and Kopalle, 2019).

Hence, the wholesale market approach and demand calibration proposed in this paper were able to capture and simulate a real world counterfactual EV charging behavior. Even when the day-night tariff would lead most households to charge from 4-5 AM, this schedule is a bit different from the welfare-maximizing hourly schedule, which charges mostly from 3-4 AM. For the day-night tariff, constraining power withdrawals with L2 chargers slightly modifies the charging schedule, and with L1 chargers, even more withdrawals must occur at 2-3 AM and at 6-7 AM.

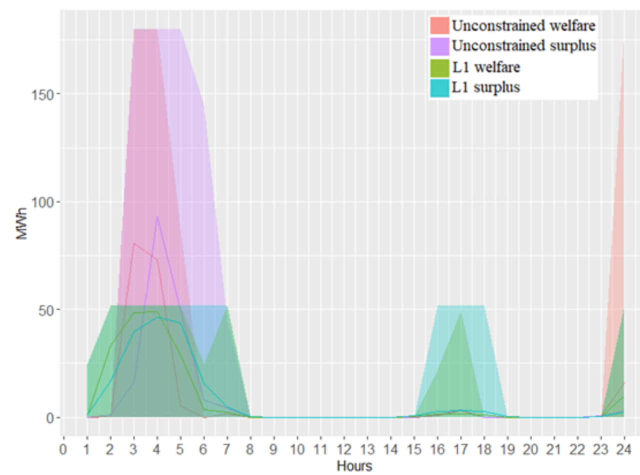
The day-night tariff charging social costs most closely resembles the first best unconstrained hourly tariffs profile since it draws most power from 3-4 AM. Hence, as long as users face full social costs, even the simple tariff can guide them to charge the vehicles efficiently.

Figure 4. EV Charging Schedules

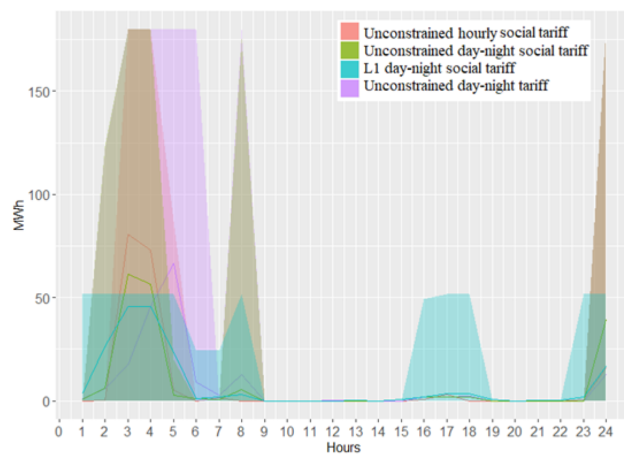
4a. Welfare-maximizing charging (hourly tariff)



4b. Surplus-maximizing charging (hourly tariff)



4c. Day-night tariff charging



Notes: The bands depict a 95 percent confidence interval, while the solid lines represent averages.

5.3 Welfare and Emissions

Unconstrained welfare-maximizing charging leads to the largest gains over current non-optimal patterns: 10.44 USD per MWh charged on average, which represents 42 percent of the average wholesale price. Constraining power withdrawals to the current Level 1 and 2 chargers limits using energy from those hours with lower prices and marginal damages, reducing welfare gains. Level 2 constrained welfare-maximizing charging leads to slightly lower welfare gains, over the non-optimal charging patterns, of 10.39 USD per MWh charged. Even under the most restrictive L1, most EV charging can be done early in the morning leading to welfare gains of 9.91 USD per MWh charged or 40 percent of the average wholesale price.[9] As EV adoption and charging demand increase, these gaps between the efficiencies of the unconstrained, L2 and L1 constrained charging will increase (Figure 5a).

On average, all welfare-maximizing scenarios lead to lower local air pollution damages (SO_2, NOx, and PM2.5) than current charging patterns. Unconstrained and L2 restricted scenarios lead to average lower carbon emissions and global damages, and L1 causes a slight increase in carbon emissions, on average (Figure 5b and 5c). Hence, the EV charging schedule that accounts for generation costs and environmental damages will reduce both in comparison to current charging patterns.

The surplus-maximizing scenarios have slightly lower gains than their welfare counterparts. Even the L1 restricted charging achieves 93 percent of the gains of the unconstrained welfare-maximizing programming. However, by not accounting for marginal damages, they all draw more power from 5-8 AM than the welfare-maximizing schedule and lead to larger carbon emissions and slightly higher local air pollution than current patterns (Figures 4b, 5b and 5c). Hence, hourly signals or prices that do not reflect the full social cost create a tradeoff between achieving reduced generation cost and increasing environmental damages.

The private generation costs day-night tariff scenarios lead to the lowest welfare of all scenarios, but still capture most gains of the welfare maximizing schedules: even the L1-constrained day night-tariff scenario captures 91.6 percent of the gains of the unconstrained first best case. Charging in these scenarios causes larger air pollution damages than those of the current

[9] Details on air pollution emissions of SO_2, NOx, and PM2.5 are in Appendix 2.

patterns and surplus maximizing scenarios. Therefore, the less granular period pricing reduces generation cost effectiveness and increases environmental damages.

On the other hand, if the day-night tariff reflects social costs, it leads to a charging profile that delivers more benefits: with unconstrained charging up to 98.3 percent of the gains of the first best. By correctly signaling users to charge from 3-4 AM it also reduces all environmental damages below those of the current charging patterns since, unlike the private costs day-night tariff, it mostly avoids any charging from 8-9 AM when emissions rise significantly (Figure 4).

The welfare and consumer surplus gains projected for all scenarios under the standard L1 (110 V) charging are the "low-hanging fruit" improvements since they can be implemented by users or households without the need of purchasing smart and or fast-charging devices. It only requires a behavioral adjustment by households that should plug in EVs not in the evening after they get home from work but later on at 12 AM and unplug them when they wake up at 7 AM. Even when the optimal charging profile varies by season (see next section), following this rule of thumb throughout the year can significantly improve welfare and capture large gains of the ideal scenarios.

At the current market price of smart chargers, even if electricity prices do not reflect emissions externalities, the welfare gains of each household under all scenarios (unconstrained, fast L2 level, hourly and day-night tariffs) are not large enough to justify buying the devices. Nevertheless, some nascent business strategies are based on aggregators grouping several households and using one smart charger to distribute EV load between several users. This can be a profitable business model since bundling the surplus gains of two households breaks even with the initial investment of the smart charger. Serving more than two users creates profitable opportunities for aggregators even if prices do not reflect emissions damages.[10]

Similarly, at the individual household level, even the welfare gains in the hourly scenario are not enough to pay for the additional cost of the L2 chargers with respect to the current standard L1 chargers.[11] However, the welfare gains that I consider do not take into account users' additional

[10] Using a 10-year lifespan of the device, the average EV charging demand in Texas based on DOT (2018), a discount rate based on private sector returns on Corporate Bonds in the United States for the last five years years (2015-2019 with an avg. of 3.734 percent using St. Louis Federal Reserve Economic Data—FRED), and 2019 market prices for smart chargers of USD 250 each based on EV Box Smart charging solution. https://evbox.com/en/products/smart-charging.

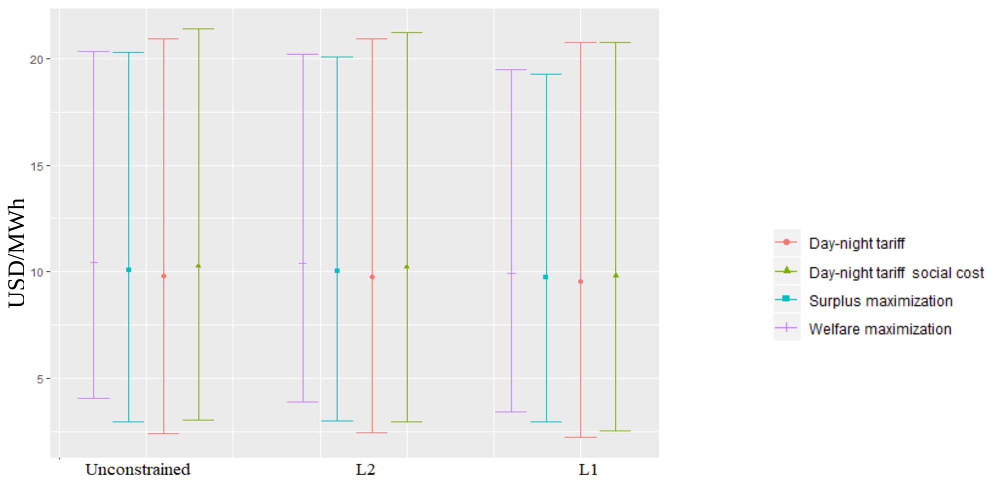
[11] Estimates based on the same parameters of the previous footnote and average market prices for L1 chargers of USD 169.99 and USD 273.57 for L2 chargers.

willingness to pay to have their vehicle charged quickly, especially during the weekends when users drive more and would rather not stay long hours at home. The incentives to adopt L2 chargers will become larger as EV penetration increases and the gains from price reductions and avoided damages become larger.

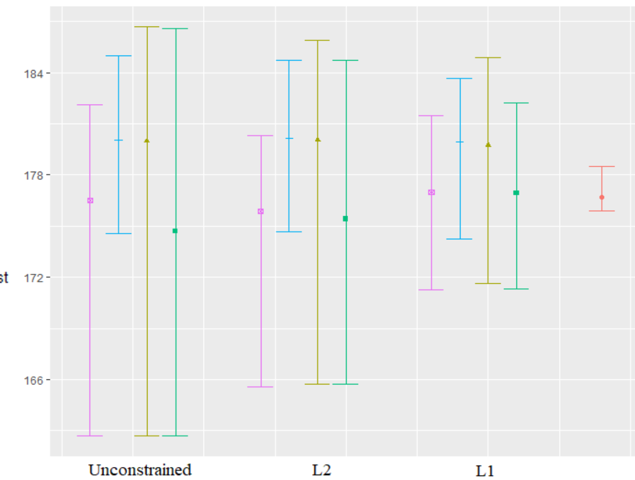
Even under the current non-optimal charging patterns of EV users, light-duty EV average CO_2 emissions per mile (176 g CO_2/mi) in ERCOT are less than half of those from the average passenger gasoline vehicle (404 g CO_2/mi) and average NOx emissions are 35.7 percent lower (0.077 lbs/mi vs 0.12 lbs/mi) (DOE and EPA, 2019; Cai, Burnham and Wang, 2013). This occurs since most of the default charging takes place during peak load (6-10 PM) when power is supplied by natural gas turbines and combined cycle plants whose fuel has a lower carbon content than gasoline from oil. On the other hand, EV's average SO_2 emissions per mile are several times larger than those of gasoline vehicles (0.14 lbs/mi vs 0.0044 lbs/mi).

Figure 5. Welfare, Carbon Emissions and Air Pollution Marginal Damages from EV Charging

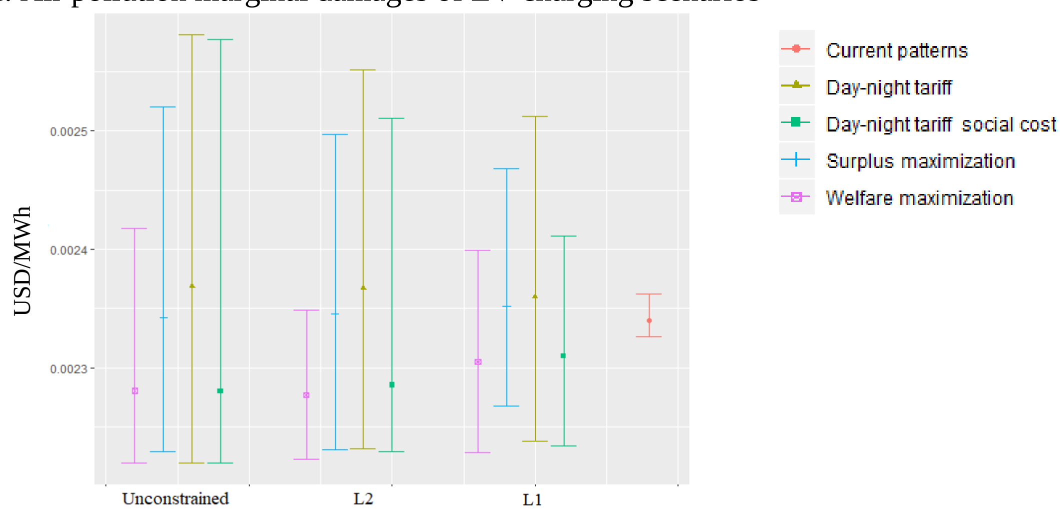
5a. Welfare gains of optimal EV charging wrt current patterns



5b. Carbon dioxide emissions of EV charging scenarios



5c. Air pollution marginal damages of EV charging scenarios

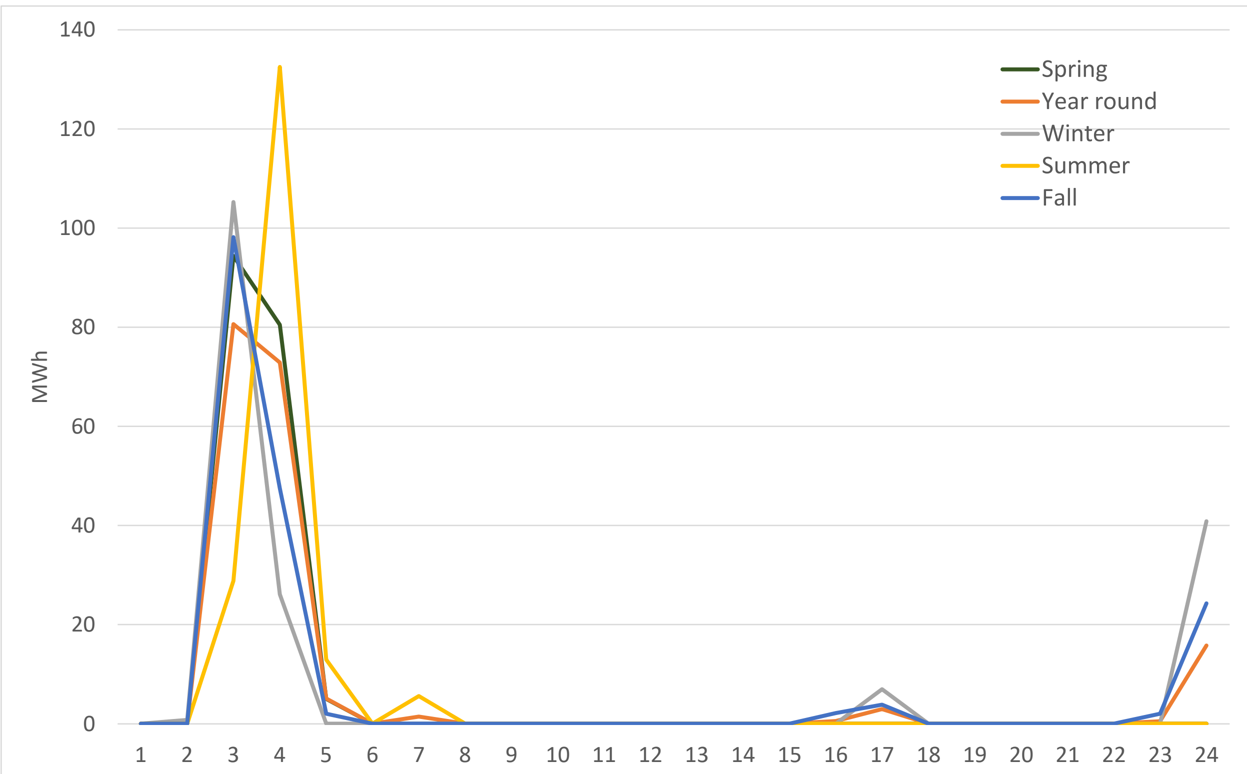


Notes: Graphs show the average and 95 percent confidence interval.

5.4 Seasonal Schedules

Wholesale electricity prices and marginal emissions vary throughout seasons due to variation in demand and the marginal generator supplying power (Figure 3d). Thus, the optimal charging schedule will also differ to account for this heterogeneity. For all seasons, the average charging profile is very similar to the average annual one with bulk withdrawals from 12-4 AM that peak between 3 and 4 AM, especially during Summer. Winter charging profiles slightly differ from the other seasons by withdrawing a larger amount of power in the afternoon (4-5 PM on average). As in the average annual results, constraining energy withdrawals leads to charging power more evenly throughout the morning (Figure 6).

Figure 6. Average Seasonal EV Charging Schedules (unconstrained welfare maximizing)



Notes: The solid lines represent averages.

6. Discussion

Charging EVs in the early morning hours delivers welfare gains in all scenarios and emissions reductions only for the welfare-maximizing schedules. Even with the slow L1 chargers and the simple day-night tariff, there are ample welfare gains which users can capture if they charge the vehicles from 1-7 AM. Hence, it is necessary to have tariffs that somehow reflect wholesale price variation and incentivize users to adopt the efficient schedules.

The key question is what tariff structure can actually promote users to adopt the least costly and polluting schedule. In principle, a tariff reflecting hourly social marginal costs is the only one that can lead to the welfare maximizing schedule or first best described in the previous section. Wolak (2011) finds that customers in Washington, DC respond in a similar way to hourly prices and to critical period pricing comprising several hours. The author reports that the percentage demand reduction of hourly and period pricing are roughly the same and that there is no economically significant cost of taking action to adjust demand in response to hourly prices.

Furthermore, even if the external validity of those results were limited, automated/smart chargers could ideally address detailed hourly signals and deliver results conveniently for users. Gillan (2017), for example, finds through a field experiment in California that electricity demand in households with smart thermostats and plugs is 56 percent more responsive to any price change than demand in households with no automation. On the other hand, responses in households with smart devices are still insensitive to price changes and do not fully resolve inattention.

Given those limitations, one could argue that users would be more responsive to the simple day-night tariff since it is based on simple heuristics and does not saturate them with too much information. Even when this tariff can deliver welfare gains to consumers, it needs to reflect full social marginal costs. Otherwise, it might very likely lead to an increase in carbon and air pollution damages compared to current evening charging patterns. The results described in the previous section can guide the design of tariffs and experiments to guide users to achieve the efficient charging schedule.

In none of the 12 scenarios is charging during workplace hours (9-16) efficient. This occurs since the lowest demand, prices and largest wind generation occur during the first hours of the day. Hence, households could conveniently charge during that time rather than during the morning and early afternoon. This finding will change if Texas significantly increases its solar capacity, which provides less than 1 percent of its electricity in 2019.

A tariff scheme by itself, even if it reflects all social costs, may not deliver the largest welfare and environmental gains of the unconstrained scenario if most users only rely on conventional charging through the home power outlet. Even when a significant share of EV users prefer charging as fast as possible, such as 40 percent in a stated preference study in England

(Daina, Sivakumar and Polak, 2017), encouraging all users to adopt fast chargers will very likely require incentives. Policies aimed at incentivizing the adoption of fast chargers are necessary to allow EV charging during those hours with the lowest fuel and environmental costs.

Furthermore, an ideal automated, smart and fast charger would allow programming power withdrawals with varying rates to charge as fast as possible but following the efficient schedule. However, it can be challenging to coordinate EV charging from all households to follow the efficient schedule. One option to achieve efficient charging is through aggregators or service providers who can make a business model of coordinating several households and arbitraging power prices (Ensslen et al., 2018).

I have argued that a day-night tariff can incentivize simple behavioral adjustments such as plugging the EV not as soon as users get home but rather later on, ideally midnight, and unplugging at 7 AM can reduce prices and environmental damages. Furthermore, aggregators who can bundle at least three users should cover the initial cost of smart chargers and still make a profit. Perhaps in the future, through advances in smart chargers and blockchain, the devices will be able to coordinate themselves.

It is worth noticing that even though I use specific marginal damages of NOx, SO_2 and PM2.5 at the county level, based on the 2011 data from the AP2 Model, the grid average marginal carbon and air pollution damages estimate that I obtain for all hours (0.031 USD/kWh) is quite close to the most recent estimate from Holland et al. (2018) for average marginal damages from 2010 to 2017 in ERCOT (0.032 USD/kWh).

The air pollution marginal damages will likely change since they depend on the total emissions and concentrations at a given time (Holland et al., 2018). The marginal carbon damages will increase as the social cost of carbon increases each year. Even under the uncertainty of which trend and effect will dominate, the key message of a timely signal for those damages through full social marginal pricing is still applicable. Furthermore, if the goal is to limit damages from emissions, then all or at least most charging should be done until 5 AM.

Even though electric vehicles are currently driven less than their gasoline and diesel counterparts in the United States (Davis, 2018), those with ample range and battery such as the Tesla models and gas/electric hybrids that are not plugged in (e.g., Prius) are driven more, on average, than gasoline and diesel vehicles in Texas (DOT, 2018). One could argue that, as the technology matures and long-range vehicles become more affordable, most household gasoline and diesel miles can be replaced by electric miles. This possibility only highlights the urgency of adopting tariffs that can incentivize users to charge optimally.

Furthermore, efficient EV charging during the first hours of the day, and not during the afternoon peak load, can avoid inefficient investment in peak power plants in the medium and long run. Efficient charging will also avoid unnecessary higher wholesale peak prices, which translates into higher tariffs in the short run. Finally, the optimal charging schedule will remain very much the same in the medium term since wind generation patterns will be the same even under larger capacities and coal power is not likely to be completely phased out in the coming years.

While the above presented results are specific for ERCOT, whose grid is mostly powered by fossil fuels with a significant share of coal, the idea of charging electric vehicles during the hours with the lowest demand and private generation cost can be broadly applied to grids mostly powered by fossil fuels. This is the case in several developing countries in Latin America and the Caribbean (e.g. Mexico, Argentina, Chile, Jamaica, Honduras) and worldwide (e.g., China, India, Nigeria).

On the other hand, assessing the best charging schedule to lower both generation cost and environmental damages will be more grid specific depending on the relevant shares of coal, oil and gas in each grid. The conceptual and empirical model presented in this paper can support such analysis. For grids, with a significant share of electricity imports the marginal emissions and damages estimates would need to track the emissions of the relevant interconnected region as proposed and done by Holland et al. (2016)

7. Conclusions

The surge in power demand for charging new EVs in Texas can be met efficiently during the first hours of the day. However, current charging patterns are the opposite due to a lack of appropriate time-variant pricing. Even a day-night and an hourly tariff based only on wholesale prices can guide users to charge their EVs at a low cost due to the concentration of low prices during the early morning hours. However, to avoid an increase in carbon and air pollution emissions, at least a day-night tariff reflecting full social costs, generation costs and environmental damages, is necessary. Furthermore, charging EVs early in the morning will cause the lowest price increase in electricity from meeting the upcoming surge in transport electrification demand and avoid unnecessary and inefficient investments in capacity.

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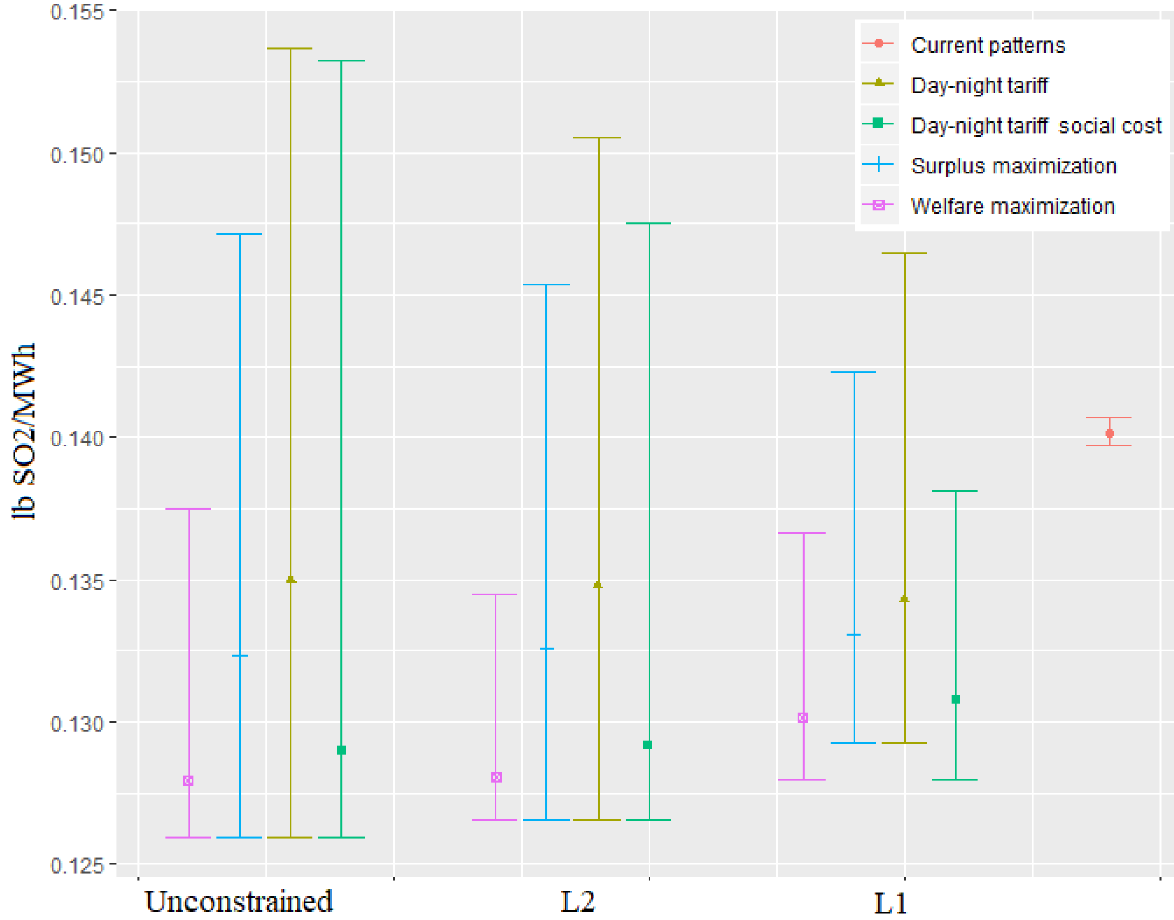
Appendices

Appendix 1. Electric Vehicles Modelling Parameters

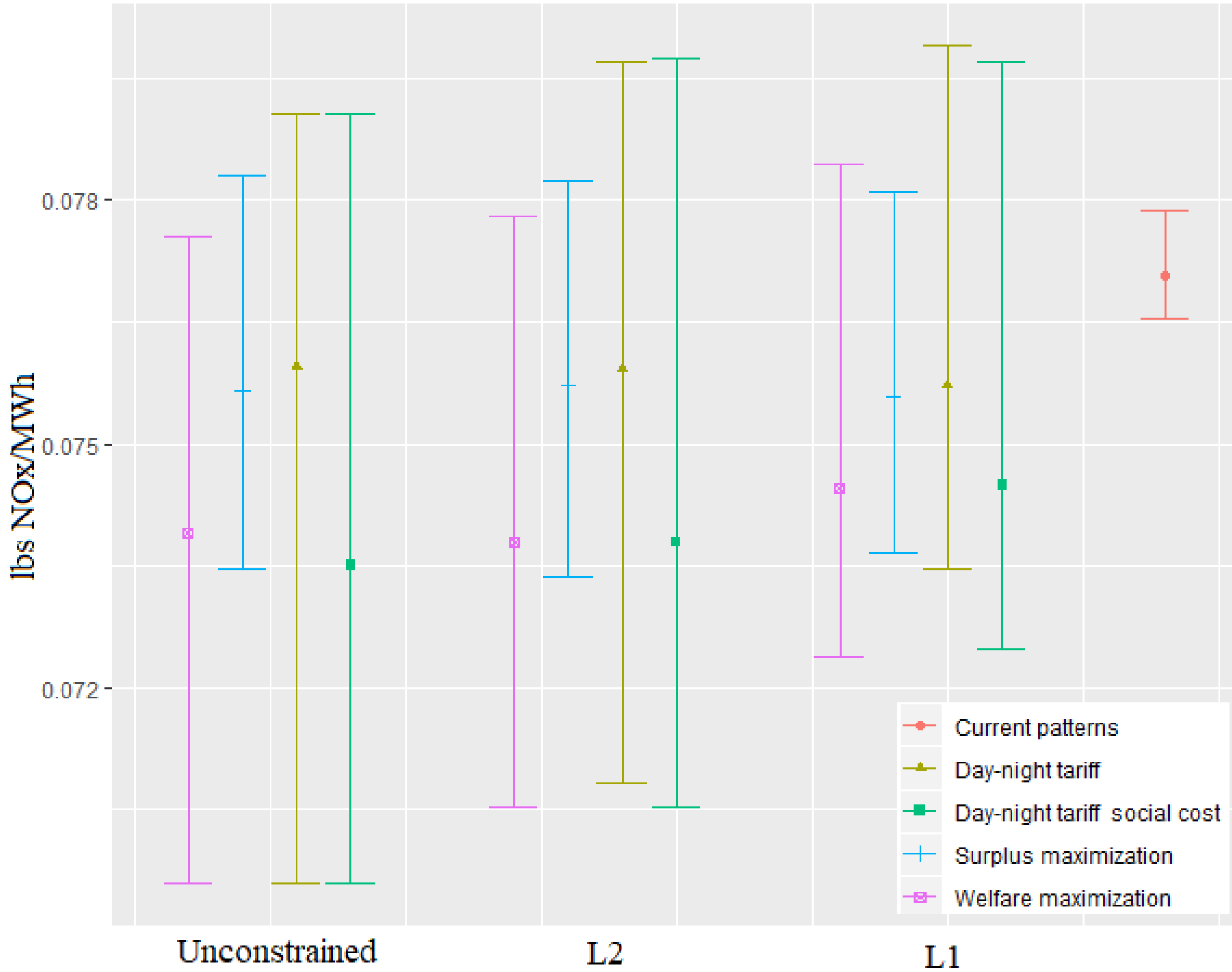
	EV type	MAKE from NHTS DOT(2018)	MODEL from NHTS DOT(2018)	Annual miles estimate from NHTS DOT(2018)	Number of vehicles estimate from NHTS DOT(2018)	Fuel economy (kWh/mi) from DOE and EPA (2019)	Ratio miles elec/miles gasoline+elect	mi/day/user	kWh/ day user	Charging restrictions kwH/L1 Level 1 ACS 15 1.4 kW (Clipper Creek, 2019)	Charging restrictions: kWh/L2 LCS 20 3.8 kW (Clipper Creek, 2019)
1	Plug-in Hybrid	12=Ford	12027=C-Max	35,407,390.00	2,726	0.38	0.0364	35.58	0.49	1.38	3.80
2	Plug-in Hybrid	19=Cadillac	NA	5,551,633.00	885	0.54	0.0705	17.19	0.65	1.36	3.56
3	Plug-in Hybrid	20=Chevrolet	20026=Volt	80,803,000.00	7,442	0.35	0.1262	29.75	1.30	1.42	4.09
4	Plug-in Hybrid	37 Honda	37031=Civic/CRX, del Sol	1,158,581.00	151	0.29	0.0228	20.96	0.14	1.34	3.35
5	Plug-in Hybrid	29	29005=Tesla	6,194,711.00	889	0.31		19.09	5.92	1.40	3.79
6	Plug-in Hybrid	51=Volvo	51401=XC90	703,758.20	114	0.58	0.0400	16.86	0.39	1.36	3.56
7	Plug-in Hybrid	12=Ford	12023=Fusion	10,797,880.00	1,012	0.38	0.0364	29.24	0.40	1.38	3.80
8	Plug-in Hybrid	49=Toyota	49046=Prius	6,377,628.00	705	0.29	0.0204	24.78	0.15	1.38	3.80
9	Plug-in Hybrid	55=Hyundai	55033=Sonata	2,460,734.00	540	0.36	0.0450	12.47	0.20	1.40	3.27
10	Plug-in Hybrid	49=Toyota	49040=Camry	41,709,460.00	957	0.29	0.0204	119.37	0.71	1.38	3.80
11	Electric	99=Unknown	NA	11,092.85	111	0.35		0.27	0.10	1.24	3.31
12	Electric	35=Nissan/Datsun	35055=Leaf	68,745,230.00	9,100	0.28		20.70	5.80	1.41	3.20
13	Electric	Tesla	29005=Tesla	85,111,250.00	5,436	0.31		42.90	13.30	1.40	3.79
14	Electric	98=Other	98998=Other (vehicle)	16,026.48	631	0.35		0.07	0.02	1.24	3.31
15	Electric	-88=I don't know	NA	172,325.80	172	0.35		2.74	0.96	1.24	3.31
16	Electric	99=Unknown	-88=I don't know	58,193.56	929	0.35		0.17	0.06	1.24	3.31
17	Electric	-8=I don't know	NA	22,504,940.00	2,340	0.35		26.35	9.22	1.24	3.31
18	Electric	49=Toyota	49402=RAV4	2,431,392.00	215	0.37		31.03	11.48	1.39	3.80
19	Electric	52=Mitsubishi	NA	4,736,659.00	516	0.26		25.14	6.49	1.39	3.20
20	Electric	34=BMW	NA	12,038,470.00	1,516	0.28		21.75	6.09	1.39	3.80
21	Electric	98=Other	-88=I don't know	12,023.84	619	0.35		0.05	0.02	1.24	3.31
22	Electric	65=Smart	65031=Fortwo	19,604.87	181	0.30		0.30	0.09	1.41	3.91
23	Electric	34=BMW	34043=1-Series	553,853.40	236	0.28		6.43	1.80	1.39	3.80

Appendix 2. Air Pollution Emissions

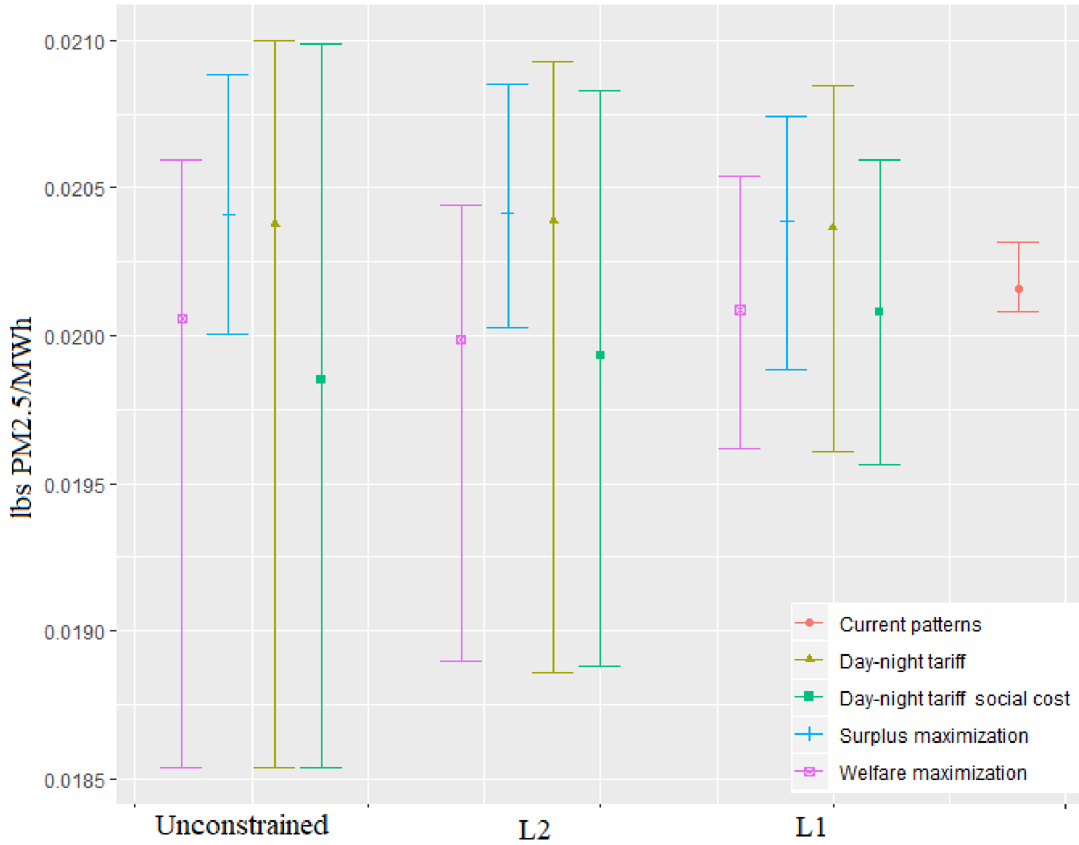
Sulfur dioxide



Nitrogen oxide



PM2.5



lbs PM2.5/MWh
0.0210
0.0205
0.0200
0.0195
0.0190
0.0185
Unconstrained
L2
L1
Current patterns
Day-night tariff
Day-night tariff social cost
Surplus maximization
Welfare maximization

Appendix 3. Carbon and Air Pollution Marginal Damages and Emissions Econometric Estimates

Newey-West standard errors with 24-hour lags

VARIABLES	Air pollution mg dmg	CO_2 mg emissions tCO_2/MWh	SO_2 mg emissions lbs SO_2/MWh	NOx mg emissions lbs NOx/MWh	PM2.5 mg emissions lbs PM2.5/MWh
1b.hour#c.Load	7.598***	0.560***	0.957***	0.514***	0.139***
	(0.359)	(0.00832)	(0.0621)	(0.0162)	(0.000895)
2.hour#c.Load	7.355***	0.561***	0.910***	0.513***	0.140***
	(0.369)	(0.00870)	(0.0641)	(0.0170)	(0.000937)
3.hour#c.Load	7.202***	0.561***	0.883***	0.515***	0.141***
	(0.376)	(0.00895)	(0.0651)	(0.0175)	(0.000968)
4.hour#c.Load	7.312***	0.570***	0.902***	0.523***	0.143***
	(0.380)	(0.00913)	(0.0661)	(0.0179)	(0.000986)
5.hour#c.Load	7.712***	0.584***	0.966***	0.544***	0.145***
	(0.384)	(0.00952)	(0.0673)	(0.0181)	(0.00103)
6.hour#c.Load	8.021***	0.590***	1.032***	0.549***	0.147***
	(0.376)	(0.00924)	(0.0656)	(0.0170)	(0.00102)
7.hour#c.Load	8.084***	0.586***	1.042***	0.547***	0.146***
	(0.356)	(0.00862)	(0.0626)	(0.0159)	(0.000986)
8.hour#c.Load	8.214***	0.594***	1.078***	0.554***	0.147***
	(0.345)	(0.00862)	(0.0608)	(0.0153)	(0.000945)
9.hour#c.Load	8.098***	0.592***	1.079***	0.550***	0.147***
	(0.328)	(0.00830)	(0.0581)	(0.0146)	(0.000926)
10.hour#c.Load	7.954***	0.591***	1.073***	0.547***	0.148***
	(0.312)	(0.00774)	(0.0543)	(0.0139)	(0.000885)
11.hour#c.Load	7.653***	0.584***	1.040***	0.553***	0.147***
	(0.295)	(0.00725)	(0.0511)	(0.0170)	(0.000838)
12.hour#c.Load	7.408***	0.578***	1.001***	0.552***	0.146***
	(0.278)	(0.00680)	(0.0483)	(0.0134)	(0.000791)
13.hour#c.Load	7.263***	0.571***	0.968***	0.566***	0.144***
	(0.264)	(0.00642)	(0.0460)	(0.0135)	(0.000742)
14.hour#c.Load	7.190***	0.565***	0.953***	0.584***	0.143***
	(0.254)	(0.00609)	(0.0443)	(0.0139)	(0.000712)
15.hour#c.Load	7.129***	0.560***	0.941***	0.591***	0.142***
	(0.249)	(0.00594)	(0.0434)	(0.0140)	(0.000694)
16.hour#c.Load	7.093***	0.557***	0.938***	0.588***	0.141***
	(0.246)	(0.00583)	(0.0431)	(0.0137)	(0.000677)
17.hour#c.Load	7.091***	0.555***	0.940***	0.573***	0.141***
	(0.248)	(0.00578)	(0.0434)	(0.0133)	(0.000675)
18.hour#c.Load	7.118***	0.555***	0.954***	0.555***	0.141***
	(0.252)	(0.00579)	(0.0443)	(0.0127)	(0.000687)
19.hour#c.Load	7.242***	0.557***	0.970***	0.540***	0.141***
	(0.263)	(0.00603)	(0.0462)	(0.0124)	(0.000710)
20.hour#c.Load	7.391***	0.563***	0.997***	0.535***	0.142***
	(0.274)	(0.00635)	(0.0479)	(0.0124)	(0.000731)
21.hour#c.Load	7.494***	0.557***	1.017***	0.522***	0.141***
	(0.281)	(0.00645)	(0.0492)	(0.0124)	(0.000747)
22.hour#c.Load	7.696***	0.557***	1.043***	0.523***	0.140***
	(0.300)	(0.00696)	(0.0522)	(0.0130)	(0.000804)
23.hour#c.Load	7.832***	0.557***	1.039***	0.524***	0.139***
	(0.325)	(0.00754)	(0.0563)	(0.0140)	(0.000853)
24.hour#c.Load	7.059***	0.517***	0.901***	0.488***	0.130***
	(0.344)	(0.00895)	(0.0596)	(0.0154)	(0.00145)

Newey-West standard errors with 168-hour lags

VARIABLES	Air pollution mg dmg	CO_2 mg emissions tCO_2/MWh	SO_2 mg emissions lbs SO_2/MWh	NOx mg emissions lbs NOx/MWh	PM2.5 mg emissions lbs PM2.5/MWh
1b.hour#c.Load	7.598***	0.560***	0.957***	0.514***	0.139***
	(0.479)	(0.0108)	(0.0841)	(0.0162)	(0.00101)
2.hour#c.Load	7.355***	0.561***	0.910***	0.513***	0.140***
	(0.497)	(0.0111)	(0.0871)	(0.0170)	(0.00106)
3.hour#c.Load	7.202***	0.561***	0.883***	0.515***	0.141***
	(0.505)	(0.0114)	(0.0882)	(0.0175)	(0.00111)
4.hour#c.Load	7.312***	0.570***	0.902***	0.523***	0.143***
	(0.513)	(0.0117)	(0.0900)	(0.0179)	(0.00115)
5.hour#c.Load	7.712***	0.584***	0.966***	0.544***	0.145***
	(0.519)	(0.0123)	(0.0922)	(0.0181)	(0.00124)
6.hour#c.Load	8.021***	0.590***	1.032***	0.549***	0.147***
	(0.509)	(0.0121)	(0.0903)	(0.0170)	(0.00125)
7.hour#c.Load	8.084***	0.586***	1.042***	0.547***	0.146***
	(0.496)	(0.0115)	(0.0871)	(0.0159)	(0.00121)
8.hour#c.Load	8.214***	0.594***	1.078***	0.554***	0.147***
	(0.480)	(0.0119)	(0.0854)	(0.0153)	(0.00117)
9.hour#c.Load	8.098***	0.592***	1.079***	0.550***	0.147***
	(0.454)	(0.0115)	(0.0814)	(0.0146)	(0.00114)
10.hour#c.Load	7.954***	0.591***	1.073***	0.547***	0.148***
	(0.435)	(0.0108)	(0.0760)	(0.0139)	(0.00111)
11.hour#c.Load	7.653***	0.584***	1.040***	0.553***	0.147***
	(0.409)	(0.0101)	(0.0717)	(0.0170)	(0.00107)
12.hour#c.Load	7.408***	0.578***	1.001***	0.552***	0.146***
	(0.382)	(0.00935)	(0.0675)	(0.0134)	(0.000994)
13.hour#c.Load	7.263***	0.571***	0.968***	0.566***	0.144***
	(0.359)	(0.00873)	(0.0634)	(0.0135)	(0.000928)
14.hour#c.Load	7.190***	0.565***	0.953***	0.584***	0.143***
	(0.346)	(0.00818)	(0.0608)	(0.0139)	(0.000883)
15.hour#c.Load	7.129***	0.560***	0.941***	0.591***	0.142***
	(0.342)	(0.00794)	(0.0596)	(0.0140)	(0.000876)
16.hour#c.Load	7.093***	0.557***	0.938***	0.588***	0.141***
	(0.340)	(0.00778)	(0.0592)	(0.0137)	(0.000845)
17.hour#c.Load	7.091***	0.555***	0.940***	0.573***	0.141***
	(0.340)	(0.00771)	(0.0594)	(0.0133)	(0.000845)
18.hour#c.Load	7.118***	0.555***	0.954***	0.555***	0.141***
	(0.349)	(0.00781)	(0.0613)	(0.0127)	(0.000892)
19.hour#c.Load	7.242***	0.557***	0.970***	0.540***	0.141***
	(0.373)	(0.00839)	(0.0658)	(0.0124)	(0.000959)
20.hour#c.Load	7.391***	0.563***	0.997***	0.535***	0.142***
	(0.389)	(0.00890)	(0.0678)	(0.0124)	(0.000968)
21.hour#c.Load	7.494***	0.557***	1.017***	0.522***	0.141***
	(0.402)	(0.00900)	(0.0691)	(0.0124)	(0.000978)
22.hour#c.Load	7.696***	0.557***	1.043***	0.523***	0.140***
	(0.421)	(0.00950)	(0.0719)	(0.0130)	(0.00100)
23.hour#c.Load	7.832***	0.557***	1.039***	0.524***	0.139***
	(0.450)	(0.0100)	(0.0771)	(0.0140)	(0.000983)
24.hour#c.Load	7.059***	0.517***	0.901***	0.488***	0.130***
	(0.468)	(0.0116)	(0.0802)	(0.0154)	(0.00189)