

ECON 8000/9000 Empirical Energy Econ

Topic 12: Introduction to Topics on EVs

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Introduction to Topics on EV

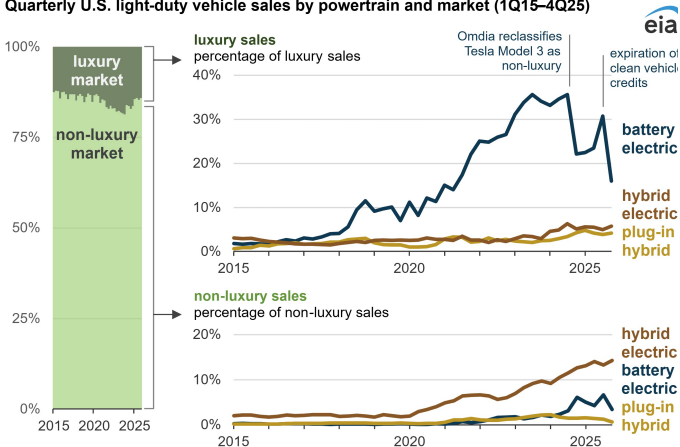
Some new considerations for EV market that are not present in ICEV market

- ▶ Consumer preference for battery range (a new attribute)
- ▶ Consumer preference for charging speed (a new attribute)
- ▶ Consumer preference for charging network + free charging spots
- ▶ Two-sided market consideration: EV adoption & charging station entry
- ▶ Early EVs market pre-predominately higher income groups as they are also luxury vehicles
- ▶ No more on-road emission! (That's why they are called zero-emission-vehicles!)
- ▶ But ZEVs are not zero emissions. Emission will then come from electricity generation
A spatial redistribution of emissions and local health impact
- ▶ Electricity consumption and smart charging
- ▶ Different regulations and incentives
 - ▶ ICEVs historically comply to fuel economy standards, CAFE by EPA and GHG emission standards by NHTSA
Now a firm with both ICEVs and EVs can use EVs to help compliance
 - ▶ Certain states have ZEV standards: 17 states
 - ▶ EV subsidies and incentives at federal and local level

Fast Facts and Discussions

1. EV uptake: Trends of market share

Quarterly U.S. light-duty vehicle sales by powertrain and market (1Q15–4Q25)

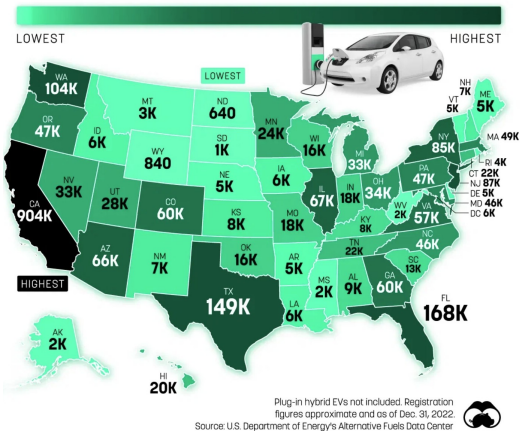


Source: US EIA

Fast Facts

1. EV uptake: Spatial distribution

The U.S. had **2.4 million** registered EVs at the start of 2023.



Source: US EIA

Fast Facts and Discussions

2. Potential Barrier: Charging Speed and Network

Electric vehicle charging

DC fast charging

non-residential



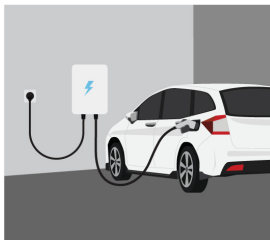
Charge time

15–45 minutes

Source: U.S Energy Information Administration

Level 2

non-residential and residential

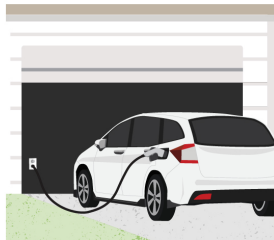


Charge time

5–6 hours

Level 1

non-residential and residential



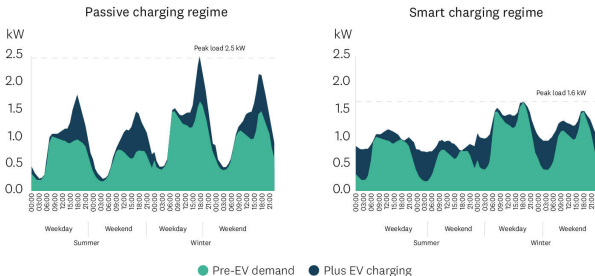
Charge time

20+ hours

Fast Fact and Discussions

4. Potential Unintended Consequences on Electricity Market + Smart Charging

Household demand under passive and smart charging regimes



Source: Concept Consulting, 2018

- ▶ Extra electricity demand
- ▶ Specifically during late hours
- ▶ An emerging technology of smart-charging: Contingent on how good AI algorithm is in automating charging by location & time

Typical Research Questions

Questions that don't involve a serious demand estimation

- ▶ Correlative question: What are typical determinants impacting EV demand?
- ▶ How do fuel & electricity price variations affect EV adoption?
- ▶ How do fuel & electricity price variations affect EV VMT?
- ▶ How does the charging network affect EV adoption & usage?
- ▶ How does the variation in electricity prices throughout the day affect EV charging time?
- ▶ What's the pass-through of EV subsidies?
- ▶ Effectiveness of adoption subsidies: Does EV subsidy increase marginal adoption or are they captured by always-adopters?
- ▶ Effectiveness of usage incentives: E.g., discounted charging from utility or local gov't
- ▶ How does EV charging affect electricity consumption and create burdens on the grid?
- ▶ How does EV adoption and charging affect emissions?
- ▶ What are the local economic impacts of charging stations (positive & negative)?

Outline

- ▶ Introduction to Topics on EVs ✓
- ▶ Example 1: Gillingham, van Benthem, Weber, Saafi, & He (2023) AEA P&P
- ▶ Example 2: Burlig, Bushnell, Rapson, & Wolfram (2021) AEA P&P
- ▶ Examples 3-4: Student Presentations: Bushnell & Rapson (2025) NBER WP + Nehiba (2024) JEEM
- ▶ Example 5: Bailey, Brown, Myers, Shaffer, & Wolak (2025) AER: Insight
- ▶ Example 6: Muehlegger & Rapson (2022) JPubE
- ▶ Example 7: Holland, Mansur, Muller, & Yates (2016) AER

Gillingham, van Bentham, Weber, Saafi & He 2021

AEA P&P "Consumer Acceptance of EV: Microdata on Every New EV Sales in US"

Research Question:

- ▶ This is a correlational study to document some patterns
- ▶ Q: If we look at demographics, what are the key determinants of EV adoption & acceptance? What types of EVs do we observe get adopted?

Data

- ▶ All new vehicle registrations from 2014 to 2020

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Burlig, Bushnell, Rapson, & Wolfram (2021)

AEA P&P "Low energy: Estimate EV electricity use"

Research Question and Data:

- ▶ RQ: How does EV adoption affect electricity consumption at different times of the day?
- ▶ Data: PG&E metering data, California DMV

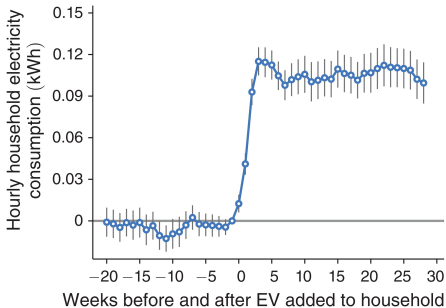
Approach: For household i in a week of the same t in hour-of-day h , estimate

$$Y_{ith} = \beta EV_{it} + \gamma Solar_{it} + \alpha_i + \delta_t + \varepsilon_{ith} \quad (1)$$

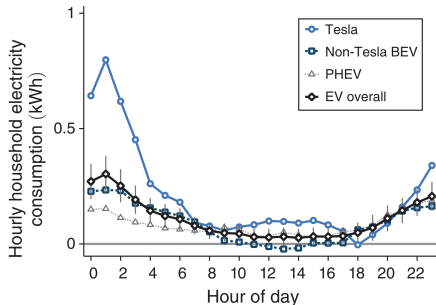
- ▶ Y : electricity consumption (kwh)
- ▶ Control: if a household has installed solar PV
- ▶ Identification: assume household i does not shift energy use across hours in a day

Results

Left: Event Study version of Eq(1)



Right: Allow β_h to vary by h in Eq(1)



- ▶ Magnitude: $\Delta 3$ kwh per day increase for EV adoptors, relative to mean at 6-10 kwh per day
- ▶ Elevated usage during peak hours

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Student Presentations

Bushnell, Muehlegger, & Rapson (2025) NBER WP:

- ▶ "Energy Price and EV Adoption"
- ▶ RQ: How does variation in fuel price and electricity price affect EV adoption?

Nehiba (2024) JEEM:

- ▶ "EV Usage, Pollution Damages, and the Electric Price of Driving"
- ▶ RQ: How does electricity price affect VMT, then ergo, pollution distribution?

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Bailey, Brown, Myers, Shaffer & Wolak (2025)

AER:I "EV and the Energy Transition: Unintended Consequences of TOU Pricing"

- ▶ For this paper, we will do a demo of making slides with Notebook LM
- ▶ I usually recommend a two-step approach
 - ▶ Step one: Ask Notebook LM to summarize the study into a deck of slides. Then you can write prompts, ask for clarification and supply some additional "sources" to perfect your deck of slides. Each iteration will take quite 10-ish minutes.
 - ▶ Optional step two: You can load the slides that Notebook LM makes for you into a different AI tool, e.g., ChatGPT, Claude, etc, and ask the AI to generate Latex code that you can copy & paste into Overleaf.
- ▶ Suitability:
 - ▶ Teach a standard set of topics for undergraduate electives. You can load relevant news, policy discussion, or simple studies that are undergrad-friendly
 - ▶ Make a deck of slides for your own research. The downside is Notebook LM doesn't generate a long deck of slides, but the slides it generates can also help you think of framing, motivation, and give you ideas regarding how to improve clarity
- ▶ Try this at your next presentation!

Bailey et al. (2025) AER:I

Iteration 1

- ▶ Prep step: Load the PDF of Bailey et al. (2025) into "Source" for Notebook LM
- ▶ Prompt *"In this chat, I would like to create a demo slides deck for Bailey et al. (2025) to show Ph.D. students how to use Notebook LM for their own studies. I will ask you to make slides, save them, then ask you for modifications, in a few iterations."*
 - ▶ Output 1: Deck V1a
 - ▶ Output 2: Deck V1b
- ▶ Pro + issues:
 - ▶ Pro: Good overview of the market if the market or policy is a bit foreign to you
 - ▶ Downside: A lot of factual errors and hallucinations. Also, the deck reads like a manifesto rather than a deck that explains a study

Bailey et al. (2025) AER:I

Iteration 2

- ▶ Prep step: crop figures, tables, and equations that are important to the study and load them into "Source" for Notebook LM to consider
- ▶ Prompt *"I have now added (i) key equation (1), (ii) figures 1-3, (iii) tables 1-2 into the source. Please revise the deck. Be clear (1) what is the experiment design, (2) what are the two key variables they look at and why they are important to look at, (3) how authors specify their estimation so that they can go after their research question, and (4) present the main results (aka Table 2 and Figure 3) and discuss implications. Also, the original slides have a lot of factual errors. For example, the total sample size is not 150; the total number of EVs is 202, with 62 EVs in control, 70 in TOU, and 70 in smart charging. I know there are 32 existing EVs, could you investigate if the main results include them or not, if so, where did the authors state so?"*
- ▶ Prompt *"Also, add how the transformer works in this research so that students understand. For example, what do transformers do and why the authors need to create "virtual" transformers."*
- ▶ Output
 - ▶ Intermediate chat responses
 - ▶ New Deck: V2
 - ▶ Much better deck but needs more work

Bailey et al. (2025) AER:I

Iterations 4-5

- ▶ Prompt *"The motivation on page 2 is fine, but that is mostly a big-picture question. The specific research question is how different types of charging pricing and systems affect when where EV users charge their vehicles. Then you can go into the big question you raised. When you raise that question, offer two solutions on the market, one is the TOU as a conventional solution that economists offered as a pricing tool, and then the second one is the managed charging. Then explain why TOU has some flaws, highlight potential (i) EV charging hours that can be created by incentivizing ppl to move to off-peak, which can create a shadow-peak, then (ii) this effect can be even worse considering the spatial correlation of such behavior. On page 4, it simply compares what 3 types of pricing as a matter of fact. The 3 rows you created are mostly your opinion. To introduce the study, just present, as a matter of fact, how the three pricing methods are implemented in general. Page 5 is great. Also, mention that transformers are hypothetical and were defined so that 2-3 EVs can be charged at the same time. Page 6, don't use the word "prove", just mention that they passed the balance test. Page 7 is great. Could you highlight beta 1 and beta 6 in one color, and beta 2 and beta 7 in another? Add a data page before the equation that lists yvars and xvars, then insert page 8 to explain what capacity violation means. No need to list page 8 after page 7 now that we explained that before the equation. For page 9, split into one slide that looks into kWh, and another that looks into constraint violation. Last page, use bullet, remove 1-5 as the questions have numbers already."*
- ▶ Prompt *"Could you add the previous version page 5 (aka experiment design) before the current page 5, i.e., explain experiment assignment first. Then add current page 7 to explain 7 var, then use current page 5 to explain the transformer. Also page 9 -12 need to insert actual figures and tables that I gave you, not to create them yourself"*
- ▶ Output: V4-V5, almost ready

Suggestions

- ▶ Cost/capacity management: Each iteration will burn some of your tokens. So if you can (i) make all requests in one go, instead of multiple iterations, and (ii) provide all "sources" needed, then the free version should be good enough. Also, you can give them some sample slides you read in the past and like for the basic structure.
- ▶ Tradeoff: 10-12 slides so some requests may crowd out other requests
- ▶ Good use: Slides deck or reports that summarize the paper
- ▶ Other use for undergrad teaching: Load your teaching slide and make some quizzes

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Muehlegger & Rapson (2022) JPubE

"Subsidizing low- and middle-income adoption of EVs: Quasi-experiment evidence from California"

Research Question: What is the effect of EV subsidies of the Enhanced Fleet Modernization Program (EFMP)?

- ▶ EFMP: A retire-and-replace subsidy since 2015
→ a bit like cash-for-clunker but for new EV adoption → takes place in 2 Air Quality Management Districts (AQMDs)
- ▶ Importance: EV adoption has been concentrated amongst the higher-income population, and subsidies have been quite regressive. → Raise issues on both (i) effectiveness ground and (ii) distributional ground
- ▶ Consumers in a disadvantaged community (DAC) receive a higher subsidy
DAC = the top quartile in terms of socio-economic disadvantages e.g., poverty, unemployment

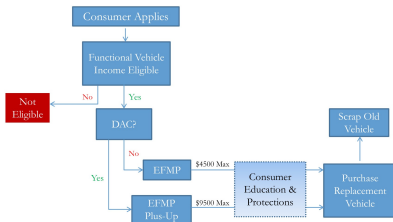
Approach and data

- ▶ DID and tripple DID
- ▶ California DMV data 2012-2018
- ▶ Program participation and rebate data
- ▶ Transactional-level data of new and used EV purchases

Program Design: EFMP

Figure A1: EFMP Eligibility Flowchart

EFMP/Plus-Up Flow Chart



10

California Air Resources Board

June 22, 2017

Table 1

EFMP Incentive Schedule for BEVs and PHEVs.

Income	EFMP Category	PHEV/BEV
< 225% FPL	Base	\$4,500
225-300% FPL	Base	\$3,500
300-400% FPL	Base	\$2,500
< 225% FPL	Plus-up	\$5,000
225-300% FPL	Plus-up	\$4,000
300-400% FPL	Plus-up	\$3,000

Other Regressions: Two-step for Elasticity

Step 1 Regression: A pass-through regression. For zipcode z in quarter t , estimate

$$Y_{zt} = \beta_1 \lambda_{zt} + \gamma_z + \nu_t + \varepsilon_{zt} \quad (1)$$

$$Y_{zt} = \beta_{PT} S_{zt} + \gamma_z + \nu_t + \varepsilon_{zt} \quad (2)$$

- ▶ Y : residual subsidy-inclusive price
- ▶ λ : fraction of vehicles subsidized in z at t
- ▶ S : average per-vehicle subsidy in z at t .
- ▶ Robustness: synthetic control
- ▶ Robustness: use θ_{At} and η_{Dt} (AQMD- and DAC-specific trend) instead of γ_z

Step 2 Regression: Quantity regression with the same IV

$$Y_{zt} = \beta_Q T_{zt}^\omega + \gamma_z + \theta_{At} + \eta_{Dt} + \varepsilon_{zt} \quad (3)$$

- ▶ Y : Inverse hyperbolic quantity of EV in z at t
- ▶ T : weighted average subsidy per EV under EFMP in z at t in two ways in 1k USD
 - ▶ High version: fraction of hh under 400% of federal poverty line (FPL)
 - ▶ Low version: fraction of hh purchased EV under EFMP

Step 3: Infer Elasticity

- ▶ Elasticity $\varepsilon_d = \frac{\beta_Q \cdot P}{\beta_{PT}}$

Additional Pass-through Results + Quantity Results

Table 4
Pass-Through and EFMP Incentives - Full Subsidy.

	(1)	(2)	(3)	(4)	(5)	(6)
	DinD	Matched DinD	Triple Diff	DinD	Matched DinD	Triple Diff
% EFMP Transactions	-8005.0*** (1348.3)	-6993.3*** (1582.1)	-7900.6*** (1343.3)			
(mean) avgsubsidy_total				-0.85*** (0.15)	-0.73*** (0.17)	-0.84*** (0.15)
Observations	12495	16415	25139	12495	16415	25139
R-Squared	0.12	0.096	0.14	0.12	0.096	0.14

The dependent variable is average residual subsidy-inclusive price in a zip*quarter, after conditioning on Make*Model*Model-year*Year of Sale fixed effects. Columns (1), (2), (4) and (5) include time and zip fixed effects. Columns (3) and (6) include time*AQMD, time*DAC and zip fixed effects. Standard errors are clustered by zip code.

Table 5
EV Sales and EFMP Incentives - Full Subsidy.

	(1)	(2)	(3)	(4)	(5)	(6)
	DinD	Matched DinD	Triple Diff	DinD	Matched DinD	Triple Diff
Lower Bound	0.028*** (0.0057)	0.016** (0.0070)	0.011 (0.0067)			
Upper Bound				0.12*** (0.011)	0.13*** (0.013)	0.11*** (0.010)
Observations	15801	19458	34477	15621	19278	34297
R-Squared	0.87	0.87	0.90	.	.	.
First-stage F-stat				170.2	120.7	168.9
Hansen Test p-value				0.64	0.33	0.89

The dependent variable is the inverse hyperbolic sine of sales in a zip*quarter. Control variables in all specifications are zip and quarter-of-sample fixed effects. Standard errors are clustered by zip code. Columns 1, 2 and 3 are OLS regressions for the unmatched Differences-in-Differences, the matched Difference-in-Differences and the Triple-differenced specifications, respectively. Columns 4, 5 and 6 present IV estimates of columns 1 through 3 using our preferred instrument described in Section 4.1.

Main Elasticity Results Again with Bounds

Table 6
Demand Elasticity of Electric Vehicles - Full Subsidy.

	(1)	(2)	(3)
	DinD	Matched DinD	DDD
Upper Bound	-3.10 (0.51)	-3.83 (0.94)	-2.83 (0.47)
Direct Estimate (IV)	-2.10 (0.46)	-2.16 (0.57)	-2.14 (0.47)
Lower Bound	-0.86 (0.22)	-0.57 (0.30)	-0.33 (0.22)

Table 6 presents elasticity estimates obtained from Eq. 15 using the "upper-" and "lower-" bound estimates from Table 5 in the top and bottom rows, respectively. Standard errors for these two rows are calculated via bootstrap (N = 200 samples drawn with replacement at the zip-code level). The middle row of Table 6 ("Direct Estimate (IV)") presents our preferred estimates of the demand elasticity, which arise from estimating Eq. 16.

- ▶ How is $\text{elas} = -2.1$ compared to early adopters?
- ▶ EV papers on earlier market (2010-2015) typically estimate EV demand elasticity -0.9 to -2
- ▶ Typical vehicle demand report elasticity -1.5 to -7
- ▶ It is indeed the case that earlier adopters' estimates are less elastic, and adopters in mid- and lower-income groups are slightly more elastic. But still not very elastic compared to typical vehicle demand
- ▶ What does that tell you about the later adopter?
- ▶ What do these results tell you about potential (i) effectiveness and (ii) regressivity of EV subsidies?

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Holland, Mansur, Muller, & Yates (2016) AER

"Are there environmental benefits from driving EV? The importance of local factors"

Research Question and Objective:

- ▶ Can we do a sophisticated accounting exercise to study the distributional effect of driving (and ergo charging) EV across various locations in the US?
- ▶ Estimate the marginal effect of charging on emissions at various power plants?
- ▶ What do these estimates imply about the optimal place-based EV subsidy?

Conception idea: Emissions from ICEVs vs EVs

- ▶ Emissions from internal combustion engine vs. emissions a combination of renewable and coal- and gas-fired combustion turbines
- ▶ What do these estimates imply about the second-best place-based EV subsidy?

Holland et al. (2016) AER

Approach

Module 1: Convert EV Charging to Emissions at plant X time level

- ▶ Correlation between hour-specific load to emissions from power plants
- ▶ You have seen an application in Nehiba (2024)
- ▶ Here they estimate β s separately for 9 NERC regions

Module 2: Convert Emissions to Damages using AP4 from Nicholas Muller

- ▶ Muller's Air Pollution Emission Experiments and Policy analysis (APEEP) model
- ▶ Later editions of APEEP are AP2, AP3, AP4 ([Link to APEEP models](#))
- ▶ A spatial accounting model started in Muller, Mendelsohn, & Nordhaus (2011) AER
- ▶ Input: emissions at different locations from various industries (power plants, various kinds of manufacturing)
 - ▶ They need Δ emissions, not just emissions.
 - ▶ Δ emissions = emissions EVs create - counterfactual ICEVs emissions avoided
- ▶ Model allows: pollutant transport and deposition
- ▶ Output: air pollution damages, such as health effects and crop yields

Holland et al. (2016) AER

Other things go into the accounting

ICEVs Emission Rate and Emissions

- ▶ This is important to compute counterfactual ICEVs emissions avoided
- ▶ Emission rate (e.g., CO₂, SO₂, NO_x) can be directly converted from fuel economy (MPG) using an engineering estimate
- ▶ They use various common sources for the engineering conversion factor
- ▶ To map emission rate to emissions, need to use VMT estimate from the EPA

What is the counterfactual ICEV vehicles

- ▶ Use the second-choice data from the MaritzCX consumer survey
- ▶ Instead of computing the diversion ratio and response matrix from estimating a discrete-choice demand model, simply use the stated preference as an estimate
- ▶ Why? A good discrete choice should be able to match the stated preference of the second choice

Empirical model

Correlate electricity use to emissions

For power plant i hourly emission at time t

$$y_{it} = \sum_{h=1}^{24} \sum_{j=1}^{J(i)} \beta_{ijh} \text{Hour}_h \text{Load}_{jt} + \phi_{mh} + \varepsilon_{it} \quad (1)$$

- ▶ Load_{jt} : electricity load in each plant i 's interconnection
 - ▶ Ideally they want to observe Load_{ijt}
 - ▶ For each of 3 interconnections, there are a few NERC region j (except TX)
 - ▶ Use hourly load at NERC region
- ▶ ϕ_{mh} : month-in-the sample FE X hour-of-day FE (36 X 24 of them)
- ▶ β_{ijh} : Marginal emission factors
- ▶ How is this connected to EV charging?
 - ▶ EV charging will shock the Load_{jt} part by different Hour_h

Empirical model

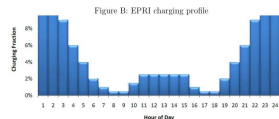
Damage estimate from Eq(1)

TABLE 1—MEAN DAMAGES IN CENTS PER MILE BY ELECTRICITY DEMAND REGION FOR A 2014 FORD FOCUS ELECTRIC VEHICLE FOR DIFFERENT CHARGING PROFILES

Region	EPRI	Flat	Hr 1–4	Hr 5–8	Hr 9–12	Hr 13–16	Hr 17–20	Hr 21–24	VMT (%)
California	0.69	0.75	0.65	0.78	0.78	0.84	0.82	0.64	11
WECC w/o CA	1.03	0.92	1.18	0.98	0.84	0.76	0.73	0.99	11
ERCOT	1.28	1.21	1.50	1.41	1.10	1.07	1.05	1.16	7
SPP	2.24	2.74	2.07	4.91	2.30	2.89	2.39	1.89	4
FRCC	2.48	2.14	3.21	2.36	2.25	1.39	1.53	2.11	6
SERC	2.75	2.67	2.75	2.26	2.72	2.96	2.63	2.71	22
NPCC	3.11	2.75	4.19	3.75	1.61	2.12	2.49	2.35	9
RFC	3.64	3.55	3.42	3.38	3.83	3.06	3.43	4.15	17
MISO & MRO	4.29	3.52	5.63	3.91	3.03	2.57	2.32	3.69	14
Total	2.59	2.41	2.90	2.56	2.28	2.15	2.12	2.46	100

Notes: The regions are ordered by the damage per mile under the EPRI charging profile. The EPRI charging profile is illustrated in Figure B in online Appendix F; the flat charging profile assumes charging is equally likely across hours; and other profiles assume charging occurs only in the indicated hours. Damages (in cents per mile) are weighted across counties by passenger vehicle VMT. California is the California ISO; WECC w/o CA is the Western United States excluding California; ERCOT is Texas; SPP is Kansas and Oklahoma; FRCC is Florida; SERC is the Southeast; NPCC is the Northeast; RFC is the Mid-Atlantic and Midwest; and MISO & MRO is the upper Midwest. See Figure C in online Appendix H for a map of the regions.

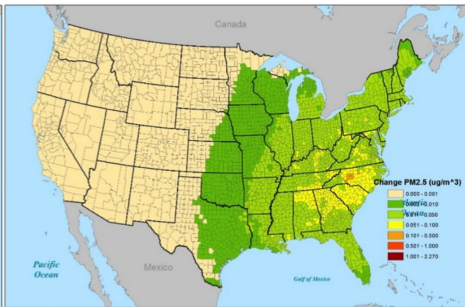
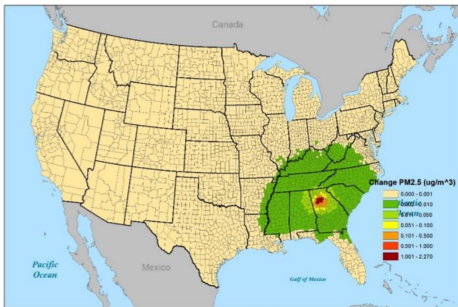
- ▶ damages weighted across hours by EPRI charging profile



Source: Electric Power Research Institute (2007).

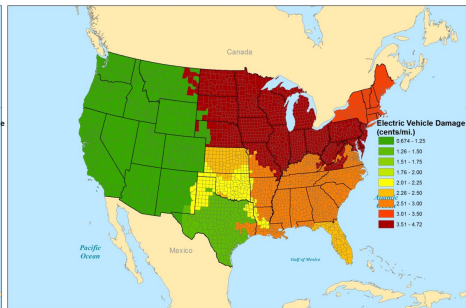
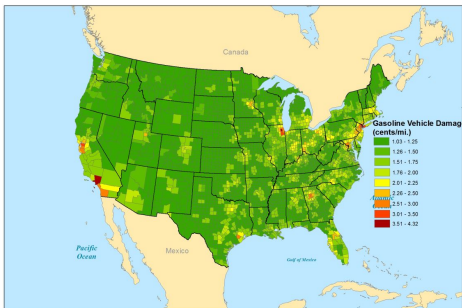
Net Damages

Spatial Example: Atlanta



Net Damages

Spatial Distribution of Using ICEVs vs EVs



Second-best Subsidy Design

Naive vs. Accounting for Emissions from Charging

