Inequality, Electric Vehicles, and Energy Transition

Qianqian (Ivy) Tang *
Emory University

March 6, 2026

Abstract: Who gains from electric vehicle (EV) adoption once affordability is explicitly modeled? I develop a static general equilibrium model with non-homothetic preferences and oligopolistic pricing in which consumers face a binding budget constraint and receive zero utility from vehicle options they cannot afford. Using 2023 California county–make–model registration data, I estimate demand, recover vehicle qualities, and invert marginal costs. The data show a steepening Engel curve for EV adoption and disproportionate entry of high-priced EV models. Counterfactuals imply that IRA-style subsidies raise consumer surplus disproportionately in high-income counties, while removing newly introduced EV models reduces adoption more in high-income counties, consistent with demand-driven up-market entry. In contrast, marginal cost reductions generate the largest adoption gains in low-income counties. These results highlight that ignoring income effects can misstate both adoption disparities and the distributional incidence of EV policies.

1 Introduction

Who buys electric vehicles (EVs) in the United States? EV adoption is skewed toward high-income households, in large part because EVs remain substantially more expensive than comparable gasoline vehicles: as of 2024, popular EV models average over $40,000, compared with roughly $33,000 for leading gasoline models. This income-based adoption gap matters for both the distribution of welfare gains from electrification and the design of clean energy policy across locations. This paper asks who benefits from EV adoption once affordability is taken seriously?

Affordability is not only a demand-side constraint. Higher willingness to pay among high-income households can also shape the supply side by encouraging manufacturers to introduce

*The author declares that they have no financial or non-financial conflicts of interest related to this research.

higher-priced EV models. This demand-driven product entry may generate a feedback loop that amplifies adoption disparities across income groups and places, with direct implications for the distributional effects of EV subsidies.

A large literature studies EV adoption and policy (Holland et al. (2016), Gillingham et al. (2022), Holland et al. (2019), Davis et al. (2023)), but it often abstracts from income effects, largely because quasi-linear utility is a common benchmark. Related work allows heterogeneity in price sensitivity across the income distribution (Sabal (2025), Grieco et al. (2024)), but typically treats income as shifting price elasticities rather than imposing an affordability constraint on discrete vehicle choices. As a result, existing approaches may miss how income shapes both adoption patterns and welfare distribution.

I build a static general equilibrium model with non-homothetic preferences and an oligopoly EV market to study how consumer surplus from EV adoption is distributed across income groups. Non-homotheticity allows income to directly affect consumers' vehicle choices. In the model, vehicle quality–reflecting new technology, reliability, driving range, charging availability and tastes–is complementary to normal goods consumption within a budget constraint, so affordability limits which options are feasible. Consumers receive zero utility from options they cannot afford, higher-income households are willing and able to pay more for higher-quality EVs, and individual income is drawn from a log-normal distribution. Compared with Berry et al. (1995), which incorporates income primarily through price sensitivity, my framework emphasizes affordability and its interaction with endogenous product offerings.

I estimate the model using 2023 California new-vehicle registration data at the county level, which allows me to estimate demand and recover marginal costs. California is the largest EV market in the United States (about 32% of U.S. EV sales), and its EV share among new light-duty vehicle purchases rose from roughly 2% in 2009 to about 25% in 2024. Estimating the model in California therefore provides a useful lens for understanding adoption patterns and the drivers of income-related disparities.

Two empirical patterns motivate the quantitative analysis. First, high-income counties not only have higher EV adoption levels, but also experience faster adoption growth (the Engel-curve slope increases). Second, a shift in product entry toward more expensive EV models relative to cheaper options.

Counterfactual simulations based on the estimated 2023 model quantify the mechanisms behind these disparities. Subsidies consistent with the Inflation Reduction Act generate larger consumer-surplus gains in high-income counties. Removing newly introduced EV models in 2023 leads to larger market-share declines in high-income counties, consistent with demand-driven up-market entry. Finally, a sharp decline in marginal costs boosts adoption

in low-income counties.

My contribution is to study welfare distribution across income groups by modeling income effects that are typically abstracted from the EV adoption literature. A central policy question is what the optimal policy for EV adoption looks like. Existing work finds that place-based policies can generate lower deadweight loss than uniform subsidies (Allcott et al. (2024), Holland et al. (2016)). However, ignoring income effects may overstate the benefits of EV adoption in low-income areas. Non-homotheticity in the model emphasizes how the income distribution shapes adoption disparities and, in turn, welfare.

2 Literature Review

This paper relates to four strands of literature. First, a large literature studies determinants of EV adoption, including electricity and gasoline prices, political ideology, and technology improvements (Bushnell et al. (2025), Archsmith et al. (2021), Davis et al. (2023), Forsythe et al. (2023)). My focus is on how income endogenously shapes adoption patterns through affordability, which is a prerequisite for vehicle purchase.

Second, research examines EV adoption and charging infrastructure, including charging-station availability and charger standards (Zhou and Li (2018), Arkolakis et al. (2025), Li (2023), Ou et al. (2020)). Standardization and expanded charging access can reduce range anxiety and lower adoption barriers. In my model, charging availability enters as a county-specific amenity, and I discipline income effects while controlling for these county-level factors.

Third, related work documents the income distribution of EV buyers and studies when low-income households benefit from EV adoption (Gillingham et al. (2023), Muehlegger and Rapson (2022), Bauer et al. (2021)). Reduced-form evidence consistently shows that EV buyers have higher incomes, but without a general equilibrium framework it misses demand-driven supply responses. If firms introduce more expensive EVs to target high-income consumers, product entry itself can feed back into adoption disparities. Methodologically, I introduce non-homotheticity following Faber and Fally (2022), Couture et al. (2024), Fajgelbaum et al. (2011), and Muehlegger and Rapson (2018).

Finally, a growing literature studies policy implications and optimal EV policy design, including work on subsidies and the Chinese EV market (Kwon (2023), Barwick et al. (2025), Allcott et al. (2024), Holland et al. (2016), Head et al. (2026), Kwon et al. (2025)). Using data from the California EV market, I study how subsidies affect welfare distribution across income groups through both demand and endogenous supply responses, a channel that remains underexplored in the existing literature.

3 Data

I use vehicle registration data from the California Department of Motor Vehicles (DMV) at the county-make-model level for 2023.[1] The Alternative Fuels Data Center (AFDC) provides detailed information on charging stations in the United States, including charger type, address, and charging network.[2] I aggregate charging stations to the county level.

I scraped manufacturer's suggested retail prices (MSRPs) for EVs from AutoBlog.[3] Vehicle subsidy information is from the Internal Revenue Service (IRS). County-level income per capita and the Gini index are from the American Community Survey (ACS) and are used to estimate local income distributions.

3.1 Income Effect

The green transportation transition is uneven: high-income counties adopt more EVs than low-income counties in California. Figure 1 shows the relationship between new EVs per 1,000 residents and income per capita. Comparing 2009 (darker dots) to 2022 (brighter dots), the slope becomes steeper over time, indicating a growing income effect: EV adoption increases substantially faster in high-income counties than in low-income counties.

3.2 Market Entry Behavior

New EV models also tend to be more upscale. I classify vehicles into two groups, above $45,000 or lower. $45,000 is roughly the average price of an entry-level luxury vehicle. Market share weighted average prices for both high- and low-price vehicles have remained relatively stable since 2010.[4] However, the number of expensive EV models entering the market has grown faster than the number of cheaper models (Figure 2). This pattern suggests that manufacturers increasingly target high-income consumers, which may widen EV adoption disparities across income groups.

3.3 Inflation Reduction Act

The Inflation Reduction Act (IRA) of 2022—the largest single investment in climate and energy in U.S. history—aims to accelerate the clean energy transition. Section 30D of the IRA provides tax credits for new, noncommercial EV purchases, subject to eligibility requirements.

[1] California Energy Commission – ZEV and Infrastructure Stats.
[2] Alternative Fuels Data Center.
[3] AutoBlog.
[4] The Tesla Roadster was the only available pure battery electric vehicle in 2009.

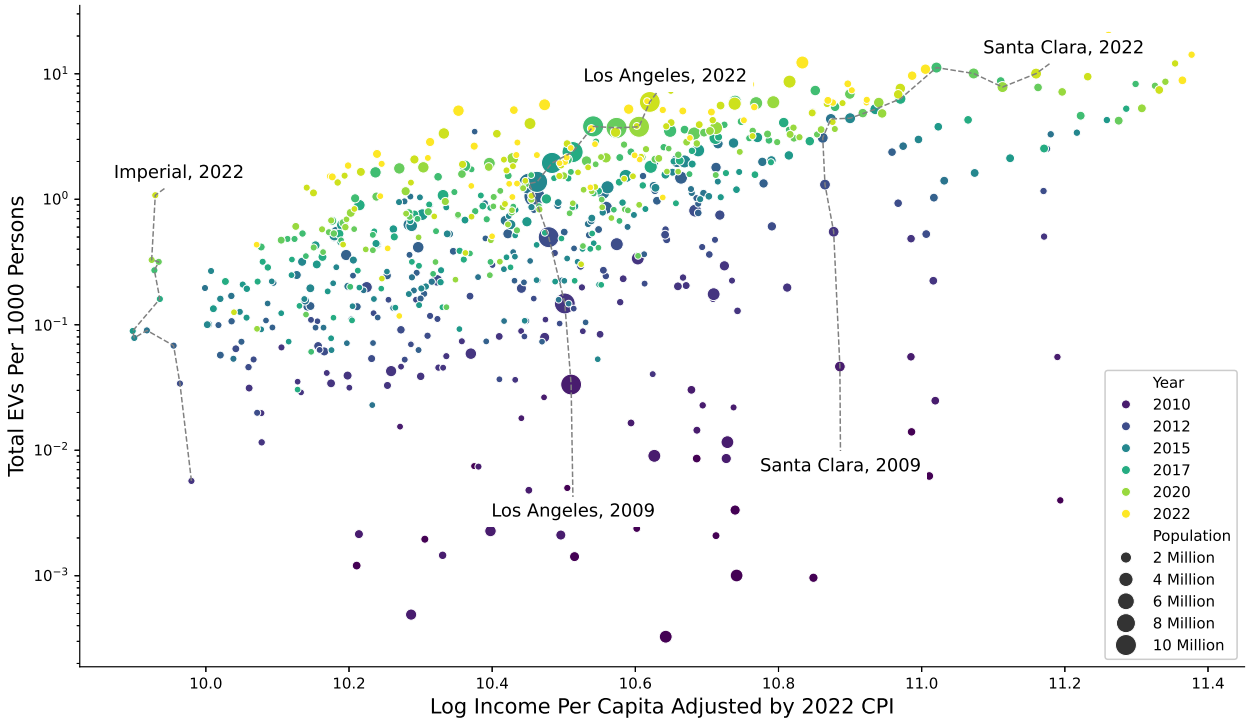
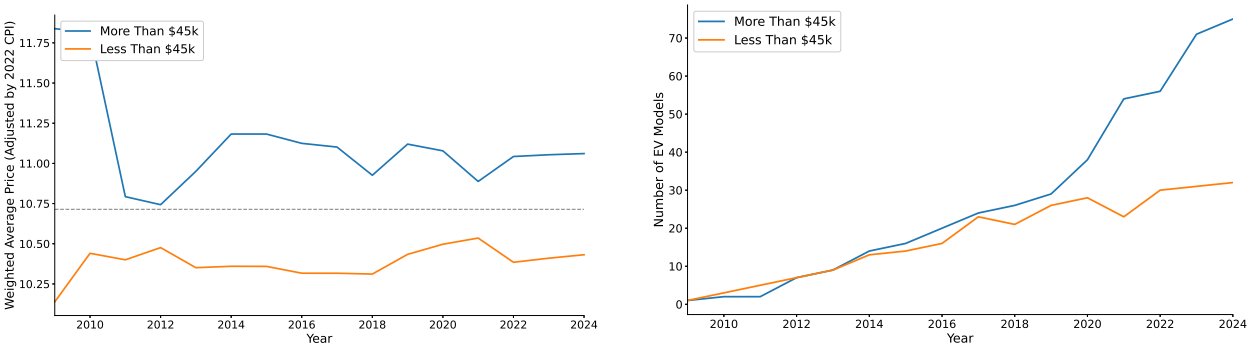


Figure 1: Electric Vehicle Adoption over Income



(a) Weighted Average Prices

(b) Number of Unique Models

Figure 2: Market Entry

Under Section 30D, eligible vehicles must weigh less than 14,000 pounds (including sedans, sport utility vehicles, and pickup trucks) and must be assembled in North America. MSRP caps apply:$80,000 for SUVs, vans, and pickup trucks, and $55,000 for other vehicles. The credit is up to$7,500 and is split into two components tied to battery requirements: $3,750 based on critical mineral sourcing (from the United States or a country with a U.S. free trade agreement) and $3,750 based on battery component manufacturing/assembly (with a minimum 50% threshold required to be manufactured or assembled in North America in 2023). In addition, consumers' adjusted gross income must not exceed $300,000 for

married couples filing jointly or $150,000 for single filers. These requirements become more restrictive over time, including provisions that exclude components sourced from a foreign entity of concern.

4 Model

4.1 Demand System

Consumer i's utility from choosing model m in county j is

$$\begin{aligned} u_{ijm} &= \log(q_{jm}) + \alpha \log(c_{ijm}) + \epsilon_{ijm} \\ s.t.:\ c_{ijm} &= y_{ij} - (p_m - \tau_m) \end{aligned}$$

where q_{jm} denotes the quality of vehicle m in county j, and I normalize the outside-option quality to $q_{j0} = 1$. The term c_{ijm} is consumption of the numeraire good.

The outside option corresponds to a non-EV, with indirect utility normalized as $U_0 = \alpha \log(y_{ij})$. The idiosyncratic taste shock ϵ_{ijm} follows a Type I extreme value (Gumbel) distribution with scale parameter 1. The model-implied market share of EV model m in county j is

$$s_{jm}(G_j, \mathbf{q}, \mathbf{p}) = \int \frac{q_{jm}(y - p_j + \tau_m)^\alpha}{y^\alpha + \sum_{l \in \text{EV}} q_{jl}(y - p_l + \tau_l)^\alpha} dG_j(y) \tag{1}$$

where $G_j(y)$ is the income distribution for each county j.

4.2 Production

I assume each model is produced by a single firm. EV producers compete in prices and choose p_m to maximize profits:

$$\begin{aligned} \pi_m &= \max_{p_m} \ x_m(p_m - c_m) \\ \text{s.t.:}\ &\sum_{j \in J} N_j s_{jm}(G_j, \mathbf{q}, \mathbf{p}) \leq x_m \end{aligned}$$

5 Estimation

In this section, I estimate demand system and recover marginal costs, including α, quality $\{q_{jm}\}$ and marginal cost $\{\text{mc}_m\}$ based on equation (1). In estimation, consumers finance vehicle purchases using a 10-year contract, so vehicle prices enter as user costs, $p_m = \frac{\text{MSRP}_m}{10}$. The adjustment of prices and income follows Holland et al. (2016) in which they multiply annual income by 10 to avoid negative $y - p$ for all consumers.

5.1 Demand Estimation

In Step 1, I guess α and use observed market shares s_{obs} and the vector of vehicle prices $\mathbf{p}$ from the data. In Step 2, I recover qualities $q_{jm}(\alpha)$ using a contraction mapping in levels (rather than logs) following Berry et al. (1995), which avoids taking logs when shares are zero:

$$q_{jm}(\alpha)^{t+1} \leftarrow q_{jm}(\alpha)^{t} \times \frac{s_{\text{obs}}}{\hat{s}(G, \mathbf{q}, \mathbf{p}, \alpha)} \tag{2}$$

Contraction mapping as in equation (2) implies $q_{jm} = 0$ whenever the observed market share of a given EV in a county is zero. To compute model-implied market shares $\hat{s}(G, \mathbf{q}, \mathbf{p})$, I integrate individual choice probabilities over a log-normal income distribution (Sabal (2025)). For each county j, the log-normal distribution is parameterized by scale

$$\sigma_j = \sqrt{2}\Phi^{-1}\left(\frac{\text{Gini}_j + 1}{2}\right)$$

and location,

$$\mu_j = \log(\text{Income per capita}_j) - \frac{\sigma_j^2}{2}$$

In step 3, I rationalize inverted qualities q_{jm} by county- and model-specific characteristics, X, such as charging infrastructure, college share, Democratic voter share, and vehicle range per charge:

$$q_{jm} = \exp\left(X_j\beta_j + X_m\beta_m + \text{charger type count}_{jm} + \vartheta_{jm}\right) \tag{3}$$

Because q_{jm} can be zero, I use Poisson Pseudo Maximum Likelihood (PPML) to estimate coefficients in equation (3). For each specification, I choose α to minimize the Poisson deviance using demeaned quality, $\frac{q_{jm}}{\bar{q}}$, which reduces sensitivity to the level (units) of $q_{jm}(\alpha)$.

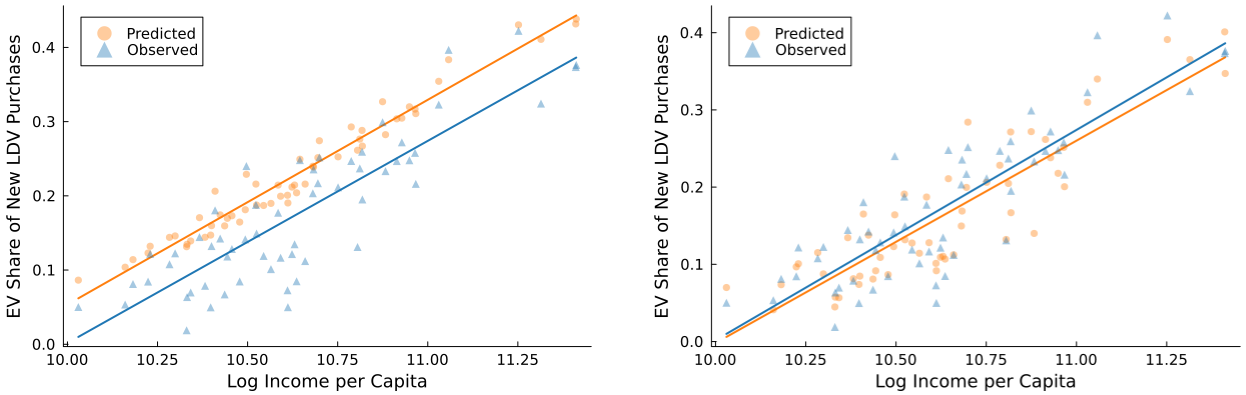
Table 1: Demand System Parameter Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	37.426	33.261	33.601	38.166	31.732	36.681	28.600	29.475
	(8.390)	(1.890)	(2.210)	(2.481)	(2.819)	(3.074)	(2.882)	(2.897)
	Quality Coefficients from PPML							
Pure Electric$_m$× ln(Total Range)$_m$				2.968***		3.550***	2.585***	2.495***
				(0.173)		(0.189)	(0.195)	(0.195)
Pure Electric$_m$		1.087***	1.876***	-16.051***	2.268***	-19.133***	-13.312***	-13.356***
		(0.034)	(0.046)	(1.039)	(0.053)	(1.133)	(1.169)	(1.170)
ln(Total Range)$_m$			1.510***	-1.061***	1.869***	-1.106***	-0.312	-0.370*
			(0.062)	(0.160)	(0.072)	(0.170)	(0.177)	(0.176)
Vehicle Type: SUV					0.691***	0.715***	0.750***	0.740***
					(0.031)	(0.032)	(0.032)	(0.032)
Vehicle Type: Pickup					-0.051	-0.206**	-0.125	-0.087
					(0.069)	(0.070)	(0.070)	(0.069)
Vehicle Type: Van					0.413***	0.511***	0.660***	0.630***
					(0.104)	(0.111)	(0.102)	(0.103)
ln(College Share)$_j$							-1.356***	-0.823***
							(0.115)	(0.125)
ln(Democrat Voter Share)$_j$							0.541***	0.609***
							(0.073)	(0.074)
ln(Specific Charger Count Per Capita+1)$_{jm}$								-0.853***
								(0.067)
ln(Parent Company Station Per Capita+1)$_{jm}$								2.333***
								(0.085)
ln(Charging Density)$_j$							0.174***	-0.011
							(0.010)	(0.017)
ln(Charging Per Capita)$_j$							-0.028	0.131***
							(0.022)	(0.028)
ln(Population)$_j$								0.258***
								(0.016)
Model Fixed Effects	Yes							
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observation	5,220	5,220	5,220	5,220	5,220	5,220	5,220	5,220
Deviance	8429.071	12522.408	11898.462	11675.696	11365.230	11092.502	11984.697	11262.222

Note: Standard errors in the parenthesis. Standard errors of α are from bootstrap.

Table 1 ireports the demand estimates. Estimations of α are robust across specifications, ranging from 28.6 to 38.166 comparable to Berry et al. (1995) and Petrin (2002).

The second panel of Table 1 displays the coefficients from quality regressions. Column (1) includes only county and model fixed effects to county-specific tastes and model characteristics. Columns (2)–(6) add vehicle observables to explain cross-model variation in quality. Conditional on being a pure EV, models with longer range have higher quality, and SUVs and vans provide higher utility than sedans. Columns (7) and (8) additionally allow tastes for the same model to vary with county demographics and charging infrastructure. Consistent with Davis et al. (2023) and Arkolakis et al. (2025), counties with higher Democratic voter shares and more charging stations per capita exhibit stronger preferences for EVs. Models produced by parent companies with denser proprietary charging networks are also more popular.



(a) Two-way Fixed Effect

(b) All Necessary Controls

Figure 3: Model Predicted and Observed Engel Curves

5.2 Model Fit

Among those specifications discussed above, Figure 3 plots predicted Engel curves in two models: a two-way fixed-effects specification in Panel (a) and a specification with the full set of controls in Panel (b). In both panels, observed market shares are shown in blue and model predictions are shown in orange. Panel (a) overpredicts market shares because the fixed effects capture average tastes for each county–model pair. Panel (b) better matches the cross-county variation in observed shares. In Table (1), Column (8) shows that pure EVs has negative effect on quality from range anxiety and local charging availability.

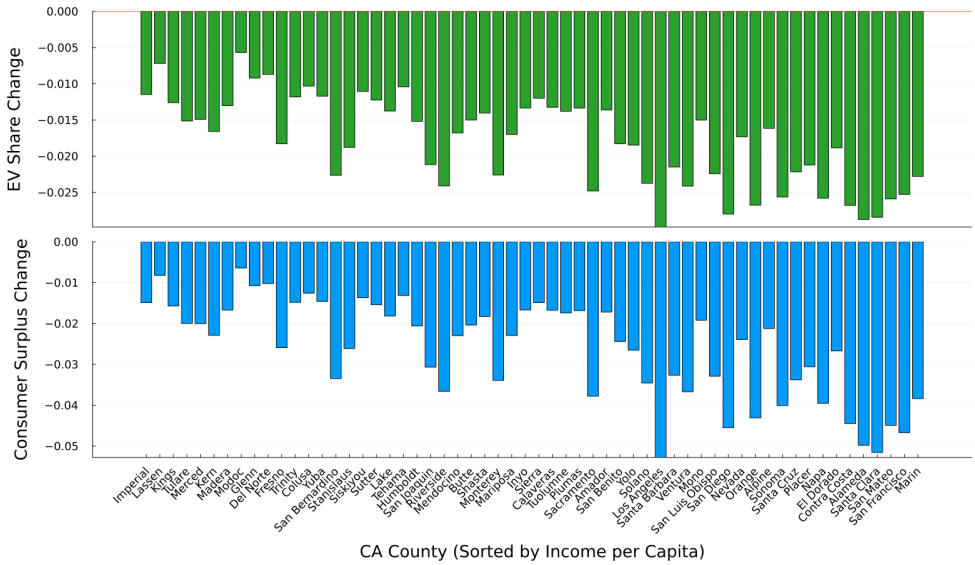


Figure 4: Consumer Surplus and EV Share Changes without Subsidy

6 Counterfactual Analysis

Using the estimated demand system, I compute semi-price elasticities for each model and recover marginal costs using MSRP data. This section evaluates three counterfactuals: removing consumer subsidies τ, removing new 2023 model entry, and reducing marginal costs.

6.1 Consumer Subsidy

Subsidies enter utility through the effective purchase price $p_m - \tau_m$. I set $\tau_m = 0$ for all counties and solve for the new equilibrium prices given marginal costs and demand. EV market shares decline in all counties due to higher purchase costs, and high-income counties experience larger declines in consumer surplus per capita (Figure 4). Because of the income effect, subsidies primarily benefit consumers who can afford EVs and who tend to have higher incomes.

6.2 Differentiated EV Subsidies

I next compare uniform and place-based subsidies. Instead of setting subsidies to zero everywhere, I keep the baseline subsidy for counties with income per capita below the median and remove the subsidy for counties above the median (Figure 5). Consumer surplus exhibits a clear pattern: counties without subsidies experience welfare losses because purchasing the same model becomes more expensive than in subsidized counties. Through equilibrium adjustments in demand and prices, EV shares increase in many low-income counties. Overall,

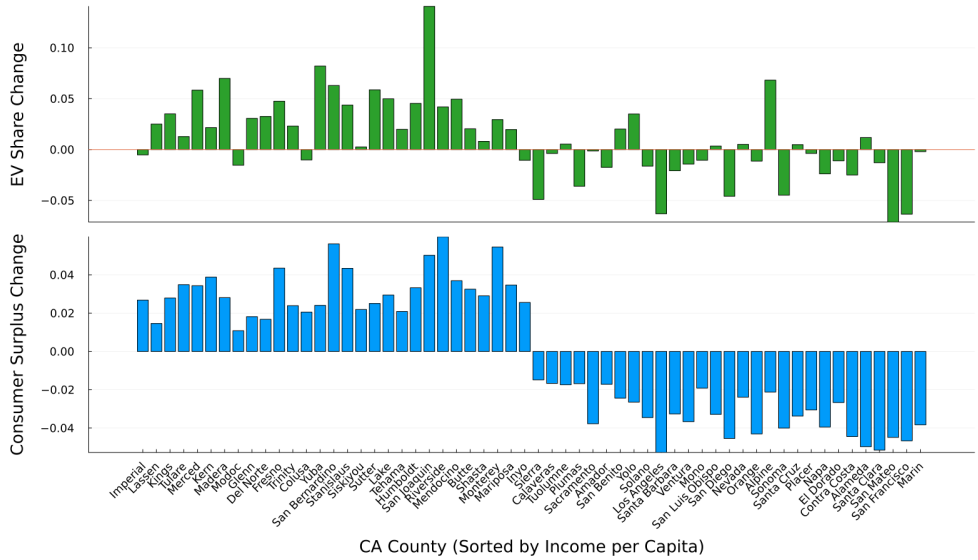


Figure 5: Consumer Surplus and EV Share Changes with Place-based Subsidy

place-based subsidies dampen the welfare gap between higher- and lower-income counties.

6.3 Market Catering

More expensive EV models have entered since 2019 relative to models priced below $45,000. To quantify the effect of manufacturers' up-market entry on adoption patterns, I remove all models introduced in 2023 (16 out of 90 models). Figure 6 shows a steeper decline in EV share changes across the income distribution, and consumer surplus falls more in higher-income counties (by more than 0.06) than in lower-income counties.

The average MSRP of new 2023 models is $66,708.47, about $1,500 higher than the average MSRP of incumbent models. Only 4 out of 16 new 2023 models are priced below $45,000. In general, higher prices coincide with higher quality. These patterns suggest that manufacturers may intensify EV adoption disparities by introducing more luxury EV models.

6.4 Comparison

Which factors contribute most to disparities in EV adoption? Figure 7 compares Engel curves across counterfactual scenarios and the observed data. Removing subsidies and removing new EV entry both flatten the positive relationship between income and county-level EV adoption. In contrast, place-based subsidies substantially reduce the adoption gap. Overall, uniform subsidies benefit high-income households more, while up-market entry amplifies the income gradient in adoption.

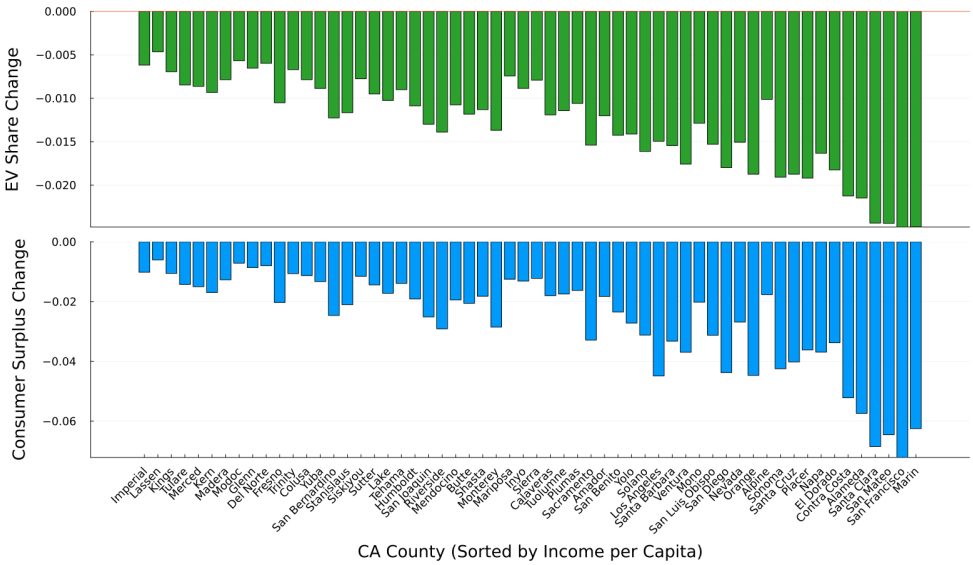


Figure 6: Consumer Surplus and EV Share Changes without New Entry

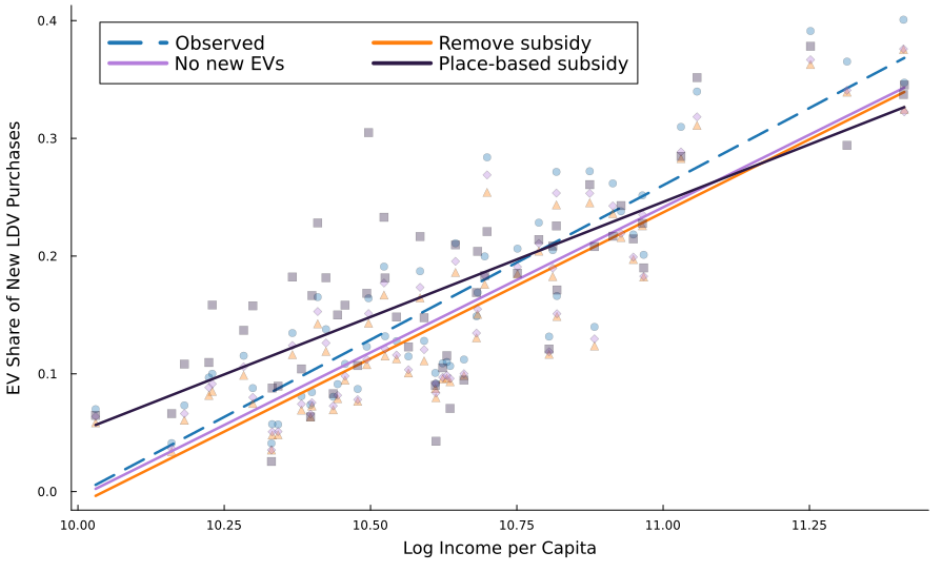


Figure 7: Engel Curves Comparison across Counterfactual Scenarios

6.5 Marginal Cost

High EV purchase prices are a key barrier for low- and middle-income households. Figures 8 and 9 show the changes in EV adoption and consumer surplus under 10% and 50% reductions in marginal costs for all models. Larger cost reductions substantially increase EV adoption in low-income counties, while high-income counties experience larger consumer-surplus gains due to higher local vehicle qualities q_{jm}.

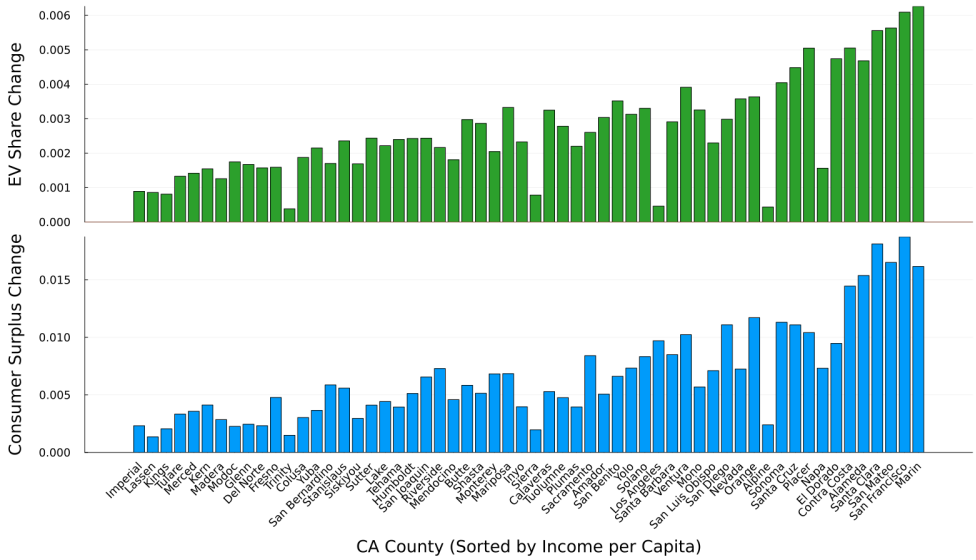


Figure 8: Consumer Surplus and EV Share Changes (10% Reduction in Marginal Cost)

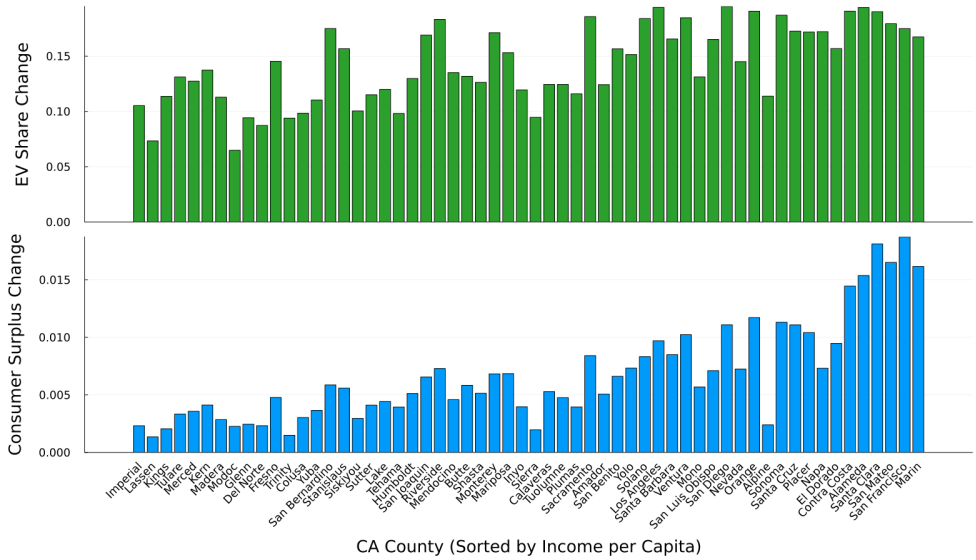


Figure 9: Consumer Surplus and EV Share Changes (50% Reduction in Marginal Cost)

7 Conclusion

This paper studies who benefits from electric vehicle (EV) adoption when affordability and endogenous market responses are explicitly incorporated. I develop a static general equilibrium model with non-homothetic preferences and oligopolistic pricing in which consumers face a budget constraint and obtain zero utility from vehicle options they cannot afford. Using 2023 California county–make–model registration data, combined with MSRP, charging infrastructure, and county-level income distributions, I estimate demand, recover vehicle

qualities, and invert marginal costs. The empirical patterns motivating the analysis are stark: EV adoption is strongly increasing in income, the adoption–income relationship steepens over time, and new EV model entry shifts toward higher-priced vehicles.

The quantitative results highlight three mechanisms shaping both adoption disparities and the incidence of policy. First, consumer subsidies similar to those in Inflation Reduction Act raise EV adoption and consumer surplus, but the gains are concentrated in high-income counties because affordability constraints limit take-up among lower-income consumers. Second, product entry is an important amplifier of inequality: removing newly introduced EV models reduces EV market shares and consumer surplus disproportionately in high-income counties, consistent with demand-driven up-market entry that caters to higher-income buyers. Third, supply-side cost reductions are the most effective channel for broadening adoption: reductions in marginal costs generate the largest increases in EV adoption in low-income counties, where affordability constraints are binding for a larger share of households.

These findings imply that policy evaluations that abstract from income effects can mischaracterize both the magnitude of adoption disparities and the distribution of welfare gains. In particular, uniform subsidies may look effective in aggregate while leaving large gaps across income groups, whereas targeted (place-based) subsidies can reduce welfare disparities by shifting benefits toward lower-income counties. More broadly, the results emphasize that EV policy should be assessed in a framework that accounts for affordability and endogenous supply responses, since firms' product positioning and entry decisions can reinforce the underlying income gradient in demand.

References

Allcott, H., Kane, R., Maydanchik, M. S., Shapiro, J. S., and Tintelnot, F. (2024). The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act.

Archsmith, J. E., Muehlegger, E., and Rapson, D. S. (2021). Future Paths of Electric Vehicle Adoption in the United States: Predictable Determinants, Obstacles and Opportunities.

Arkolakis, C., Gillingham, K. T., and Yoo, S.-Y. (2025). Optimizing Electric Vehicle Infrastructure. *AEA Papers and Proceedings*, 115:563–567.

Barwick, P. J., Kwon, H.-S., Li, S., and Zahur, N. B. (2025). Drive Down the Cost: Learning by Doing and Government Policies in the Global EV Battery Industry.

Bauer, G., Hsu, C.-W., and Lutsey, N. (2021). When might lower-income drivers benefit from electric vehicles? Quantifying the economic equity implications of electric vehicle adoption.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841.

Bushnell, J., Muehlegger, E., and Rapson, D. S. (2025). Energy Prices and Electric Vehicle Adoption.

Couture, V., Gaubert, C., Handbury, J., and Hurst, E. (2024). Income Growth and the Distributional Effects of Urban Spatial Sorting. *Review of Economic Studies*, 91(2):858–898.

Davis, L. W., Li, J., and Springel, K. (2023). Political Ideology and U.S. Electric Vehicle Adoption.

Faber, B. and Fally, T. (2022). Firm Heterogeneity in Consumption Baskets: Evidence from Home and Store Scanner Data. *The Review of Economic Studies*, 89(3):1420–1459.

Fajgelbaum, P., Grossman, G. M., and Helpman, E. (2011). Income Distribution, Product Quality, and International Trade. *journal of political economy*.

Forsythe, C. R., Gillingham, K. T., Michalek, J. J., and Whitefoot, K. S. (2023). Technology advancement is driving electric vehicle adoption. *Proceedings of the National Academy of Sciences*, 120(23):e2219396120.

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J., and Schjerning, B. (2022). Equilibrium Trade in Automobiles. *Journal of Political Economy*, 130(10):2534–2593.

Gillingham, K. T., Van Benthem, A. A., Weber, S., Saafi, M. A., and He, X. (2023). Has Consumer Acceptance of Electric Vehicles Been Increasing? Evidence from Microdata on Every New Vehicle Sale in the United States. *AEA Papers and Proceedings*, 113:329–335.

Grieco, P. L. E., Murry, C., and Yurukoglu, A. (2024). The Evolution of Market Power in the U.S. Automobile Industry. *The Quarterly Journal of Economics*, 139(2):1201–1253.

Head, K., Mayer, T., Melitz, M., and Yang, C. (2026). Industrial policies for multi-stage production: The battle for battery-powered vehicles.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016). Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. *American Economic Review*, 106(12):3700–3729.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2019). Distributional Effects of Air Pollution from Electric Vehicle Adoption. *Journal of the Association of Environmental and Resource Economists*, 6(S1):S65–S94.

Kwon, H.-s. (2023). Subsidies versus Tradable Credits for Electric Vehicles: The Role of

Market Power in the Credit Market.

Kwon, H.-s., Allcott, H., and Snyder, T. (2025). Equitable Energy Transitions? The Efficiency and Distributional Effects of Subsidies for Used Electric Vehicles. *SSRN Electronic Journal*.

Li, J. (2023). Compatibility and Investment in the U.S. Electric Vehicle Market.

Muehlegger, E. and Rapson, D. (2018). Understanding the Distributional Impacts of Vehicle Policy: Who Buys New and Used Alternative Vehicles?

Muehlegger, E. and Rapson, D. S. (2022). Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *Journal of Public Economics*, 216:104752.

Ou, S., Lin, Z., He, X., Przesmitzki, S., and Bouchard, J. (2020). Modeling charging infrastructure impact on the electric vehicle market in China. *Transportation Research Part D: Transport and Environment*, 81:102248.

Petrin, A. (2002). Quantifying the Benefits of New Products: The Case of the Minivan. *Journal of Political Economy*, 110(4):705–729.

Sabal, A. (2025). Product Entry in the Global Automobile Industry.

Zhou, Y. and Li, S. (2018). Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market. *The Journal of Industrial Economics*, 66(2):423–480.