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The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act

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Abstract

We provide the first ex post microeconomic welfare analysis of the electric vehicle (EV) tax credits in the Inflation Reduction Act (IRA). Relative to pre-IRA policy, the credits generated \$1.96 in domestic benefits per dollar of government spending, with taxpayer cost of \$36,500 per additional EV. Relative to having no EV credits, they yielded \$1.11 in domestic benefits per dollar of government spending. A leasing loophole that sidestepped domestic content rules created negative domestic benefits. A prominent example of green industrial policy, the credits harmed foreign countries by shifting surplus to domestic producers and helped them by decreasing CO_2 emissions.

JEL Codes: F18, H23, L11, Q58.

Keywords: Electric vehicles, Inflation Reduction Act, green industrial policy, trade restrictions, environmental taxes and subsidies, trade and the environment.

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1 Introduction

The Biden Administration billed the Inflation Reduction Act (IRA) as the "most ambitious investment in combating the climate crisis in world history" (White House 2023). In addition to addressing climate change, policymakers designed the IRA to protect domestic manufacturing and secure supply chains so as to be politically sustainable across elections. The IRA relied heavily on uniform tax credits for low-carbon technologies made in the US and allied countries. Tax credits for electric vehicles (EVs) provided a central component of the IRA. Bistline, Mehrotra, and Wolfram (2023) and the Committee for a Responsible Federal Budget (2023) projected that the EV credits would cost \$70 to \$390 billion over a decade, up to half of the IRA's projected total cost. The IRA, however, had a limited lifetime, as the One Big Beautiful Bill Act ended the EV credits in September 2025. Meanwhile, some progressives have demanded an "IRA 2.0" and Europe is advancing its own "Industrial Accelerator Act," which in some ways echoes and responds to the IRA (Worland 2024; Jensen 2025).

The EV tax credits offer a fascinating case study of combining climate and industrial policy. To encourage a transition to EVs while reducing China's dominance of manufacturing and battery supply chains, the IRA restricts tax credits for *purchased* EVs to vehicles assembled in North America that contain a sufficiently large share of battery inputs from the US or allied countries (excluding China). Equally generous credits to companies for *leasing* EVs lack these restrictions, generating a "leasing loophole." As we discuss, the IRA substantially prioritizes US production, part of a longstanding "Buy American" federal policy goal that the Biden Administration has expanded. Yablon (2023) summarizes tensions this created:

> Many of the US's allies like Japan, Canada, and especially the European Union have not been all-in. They see the Biden administration's signature accomplishments – such as the Inflation Reduction Act (IRA) – less as long-awaited efforts to finally make good on promises of climate action and more as a threat to the ability of places like Europe to attract investment themselves. ... After decades of pleading with America to finally take action on issues such as climate, why are our closest partners so annoyed at us now that we're actually doing what they asked?

French President Emmanuel Macron, for example, lauded the IRA's "common objective" in transitioning to green energy and lamented its "super aggressive" stance towards European Union firms (France 24 2022; Rose and Mason 2022).

This paper's primary goal is to characterize the market and welfare effects of actual and counterfactual policy in this context for a social planner that may prioritize domestic over foreign producer surplus. In the process, we discuss tradeoffs that this prominent example of green industrial policy creates between trade and the environment and between domestic and foreign interests. The EV credits combine a non-cooperative, national welfare perspective on producer surplus that encourages profit shifting, together with more cooperative investment in the global public good of CO_2 mitigation that benefits the planet.

Our analysis uses a uniquely extensive combination of vehicle market data. We combine proprietary transaction-level dealership microdata from Cox Automotive, monthly national new vehicle registrations by detailed model trim ("submodel") and lease status from Experian, aggregate supply conditions data from Edmunds, second choice survey data from Strategic Vision, registration microdata from two US states (California and Texas), archival web scraping records for Tesla, original surveys we conducted with over 250 dealerships, administrative air pollution measurements for new gasoline vehicles (GVs), and administrative credit eligibility from the US Treasury Department, plus more standard data sources. These records allow a deeper analysis of clean vehicle tax credits and vehicle trade-environmental policy than has previously been possible.

We begin by describing externalities within EV and within GV submodels. For each submodel, we calculate CO_2 emissions from manufacturing and scrap ("cradle to grave"), CO_2 and local air pollution emissions from driving, externalities from fatal accidents, and fiscal externalities from explicit or implicit taxes on gasoline and electricity. Our calculations reflect typical assumptions such as a \$241 social cost of carbon (US EPA 2023) and other marginal damages building on Holland et al. (2016). We also report results when applying a US domestic social cost of carbon (Ricke et al. 2018). Sensitivity analyses consider long-run marginal emission rates from the electricity grid. We find comparable heterogeneity within EV submodels as within GV submodels, and substantial overlap between the EV and GV externality distributions. This finding conflicts with the prevailing approach of promoting substitution from GVs to EVs (vehicle electrification) as the critical policy objective to address externalities, without attention to which EVs consumers choose.

To evaluate the EV tax credits' short-run impacts, we use event study analyses. Under Section 30D of the US tax code, EV buyers with incomes below a threshold could receive \$7,500 income tax credits for buying eligible vehicles. EVs assembled outside of North America lost eligibility in August 2022. With the implementation of battery sourcing requirements, purchases of many other vehicles lost eligibility in April 2023. Beginning in January 2023, leased EVs became eligible for credits, even if the EVs were assembled outside North America and regardless of household income. Regressions suggest that consumers capture a meaningful share of the credits' incidence, though we interpret event study estimates for vehicle purchase prices cautiously since supply chain constraints potentially affected prices, particularly in mid-2022. Driven by the decreased price of leasing relative to buying, EV markets shifted significantly toward leasing throughout 2023. Vehicles assembled outside of North America, which lost eligibility for credits in August 2022 but gained eligibility when leasing in January 2023, had remarkable shifts to leasing of roughly 50 percentage points.

To study counterfactual scenarios and perform welfare analysis, we use an equilibrium model. The model has nested logit demand with preference heterogeneity across incomes, an exogenous choice set, constant marginal costs, and static Nash-Bertrand pricing. This framework is appropriate for predicting effects over a short- to medium-term horizon—long enough to ignore temporary inventory constraints but short enough to ignore supply chain adjustments, new model entry, or learning-by-doing. We design the demand system to have flexible substitution patterns on the four margins most important for evaluating the IRA EV tax credits: substitution from EVs to GVs, across vehicle classes, between buying and leasing, and across vehicle submodels. We model heterogeneous consumer types to match overall patterns in the vehicle market that vary by income. We calibrate the substitution parameters to match empirical moments from the leasing event studies, second choice data, and price sensitivity estimates from Grieco, Murry, and Yurukoglu (2024).

We find that repealing the IRA EV credits or replacing them with pre-IRA credits pits trade versus the environment—these reforms benefit foreign countries by undoing the IRA's profit shifting incentives, but harm them by increasing CO_2 emissions. Eliminating all EV credits increases foreign firms' share of EV registrations by a third (increasing trade) and decreases total EV registrations by a fifth (harming the environment). Returning to pre-IRA credits has smaller magnitudes but some similar patterns. The IRA spends $26,500 to $36,500 per incremental EV sold, partly because 72 to 84 percent of credit recipients would have chosen an EV even without the credits (i.e., these credits are inframarginal and so not additional). From the US planner's perspective, switching from no EV credits to the IRA credits has a marginal value of public funds (MVPF) of 1.11 to 1.28. But replacing pre-IRA EV credits with the IRA EV credits has an MVPF of 1.96 to 2.22, which is higher partly since pre-IRA policy mostly subsidized foreign vehicles. Interestingly, relative to pre-IRA policy, the IRA EV credits have a higher MVPF from the US planner's perspective than from the global planner's perspective. This is unusual for a climate policy, since the usual logic of investing in a global public good like CO_2 mitigation is that the global planner benefits more than the domestic planner. This setting reverses that standard logic because it involves profit shifting, and the incentive to shift producer surplus across borders outweighs the free rider incentive that typically discourages greenhouse gas mitigation.

Since the IRA pursued a broad set of objectives, we also calculate the credits' impact on employment and manufacturing. We find that repealing the credits decreases US auto assembly and parts employment by 12,000 to 15,000 jobs, from a baseline of approximately 850,000 workers. These credits end up spending $169,000 or more per auto industry job created, suggesting that this policy is not particularly cost-effective solely as an employment program. Repealing the credits decreases the number of EV batteries assembled domestically by about 250,000. The long-run capacity investment capable of producing the increase in US-assembled EVs that we estimate is in the range of $2.4 to $4.0 billion, in the ballpark of one or possibly two additional large plants.

We also study three other sets of counterfactual changes—to the EV credits' trade restrictions, income restrictions, and credit magnitudes. Counterfactuals that equalize trade restrictions between leases and purchases close most of the leasing loophole, though they preserve the incentive to lease to avoid income restrictions. The leasing loophole performs poorly, with an MVPF of 0.45 to 0.68 from either the US or global planner's perspective. The leasing loophole is not a cost-effective way to relax trade restrictions because our substitution patterns imply that many people who lease foreign EVs in order to claim IRA incentives through the loophole would have either bought a domestic EV or an unsubsidized foreign EV instead. Thus, the leasing loophole transfers producer surplus to foreign firms while increasing EV take-up little. Removing trade restrictions from purchases would reduce domestic welfare when evaluated under a domestic social cost of carbon, but benefit the environment and increase US welfare when applying the global social cost of carbon. We generally find that "Buy American" provisions decrease the credits' environmental benefits. While broader debates contest how trade affects the environment, in this setting, trade increases the market share of a good (EVs) that decreases CO_2 emissions.

Counterfactuals that remove the income restrictions have moderate benefits, though they are regressive. Removing the income restrictions increases the number of US EVs sold, transfers surplus to domestic producers, decreases CO_2 emissions, and obtains an MVPF of 1.46 to 1.79. This reform also decreases leasing among high income households, since they leased partly to avoid the income restrictions. We estimate that the income restrictions only drove 15 percent of the aggregate shift to leasing, with 85 percent due to trade restrictions.

Finally, we consider counterfactuals that change the magnitudes of the EV credits. We calculate the constrained optimal subsidy that maximizes total surplus in our framework, holding fixed the list of models eligible for purchase credits. We decompose the constrained optimal subsidy into three terms: the net distortion (markup minus negative externality); indirect substitution from non-subsidized vehicles; and profit shifting from foreign to domestic firms. We analyze both a heterogeneous subsidy that differs by submodel and a uniform subsidy that does not; the two formulas have similar structure but the uniform version uses demand-response weighted averages across models.

We find that both the sign and magnitude of these constrained optimal subsidies depend on political economy considerations. Under a global social cost of carbon, first-best policy would tax all vehicles, since both EVs and GVs have negative externalities that exceed markups. If political economy or other forces prevent taxes on GVs, however, the sign of optimal policy reverses—it becomes optimal to subsidize EVs in order to induce substitution from GVs, which on average have higher externalities than EVs. Under simplifying assumptions, including non-distortionary taxation, a uniform EV subsidy of $9,606 maximizes US total surplus. This exceeds the actual $7,500 subsidy, though not dramatically so. Our decomposition indicates that the profit-shifting component accounts for 40 percent of this value, so noncooperative motivations matter for subsidy magnitudes. If taxation generates deadweight loss, the constrained optimal subsidy is much lower. Differentiated subsidies reflecting submodel-specific externalities obtain about 30 percent higher welfare effects than uniform subsidies.

Our paper has several important limitations. Because we analyze the short- to medium-run, we abstract from effects of EV tax credits over the long-term, when automakers might adjust along these margins. We also ignore US trading partners' potential retaliatory trade restrictions. Short- to medium-run analysis is important given ten-year budgeting horizons in the US Congress, a two- to six-year election cycle, rapid developments in EV policies and investments, potential future debates about consequences of resuscitating the credits, and of course the IRA EV credits' three-year lifetime before the One Big Beautiful Bill Act cut them. Additionally, while we measure externalities carefully, results reflect our externality assumptions. For example, we do not account for decreased noise externalities from EVs or pollution from the tire wear caused by heavier vehicles, though we do include other weight-related externalities.

We contribute to a nascent literature studying the IRA and to analyses of prior US tax credits for clean vehicles by providing the first ex post empirical microeconomic welfare evaluation of the IRA's EV tax credits. These credits were designed to be one of the most significant environmental policies in US history and a leading example of US trade and environmental policy. This literature includes policy overviews (Bown 2023; Buckberg 2023), reduced-form and structural evaluations of previous state and federal credits (Chandra, Gulati, and Kandlikar 2010; Sallee 2011; Gallagher and Muehlegger 2011; Jenn, Azevedo, and Ferreira 2013; Jenn, Springel, and Gopal 2018; Clinton and Steinberg 2019; Sheldon and Dua 2019; Xing, Leard, and Li 2021; Muehlegger and Rapson 2022; Lohawala 2023), and ex ante evaluations of the IRA credits (Bistline, Mehrotra, and Wolfram 2023; Cole et al. 2023; Slowik et al. 2023; Hahn et al. 2024). Four working papers model long-run benefits: Linn (2022) models US EV credits in a model with endogenous entry of new vehicles, Head et al. (2026) model reallocation of EV supply chains in response to the IRA, and Barwick, Kwon, and Li (2024) and Barwick et al. (2025) focus on the effects of Chinese EV tax credits in models of endogenous attributes or learning-by-doing. Cox and Acosta (2023) and Bombardini et al. (2024) study general costs of Buy American provisions in federal procurement. Our estimate of subsidy additionality echoes recent estimates of environmental policy additionality in disparate settings (Arkolakis and Walsh 2023; Aspelund and Russo 2024; Chen, Ryan, and Xu 2024). More broadly, our timely retrospective analysis, not long after the IRA's passage and soon after its effective repeal, somewhat echoes timely retrospective analysis of Trump tariffs and COVID lockdowns (Fajgelbaum et al. 2020; Flaaen, Hortaçsu, and Tintelnot 2020; Chetty et al. 2024; Gopinath and Neiman 2026).

We also provide the first theoretical and empirical analysis of profit shifting and the environment. We describe optimal domestic subsidies or taxes for differentiated, traded products in concentrated industries, then empirically calculate these subsidies and decompose them into net distortions, indirect substitution, and profit shifting. We also distinguish the role of profit shifting in welfare analysis of the actual IRA EV credits and contrast welfare consequences from the perspective of global versus national planners, for foreign and domestic producer surplus versus environmental externalities, and for local versus global externalities. Unilateral trade policy in imperfectly competitive markets can transfer surplus from foreign to domestic firms (Brander and Spencer 1981; Brander and Spencer 1984; Venables 1985; Bagwell and Staiger 2012). Quantitative models of trade and the environment typically assume perfect competition (Costinot, Donaldson, and Smith 2016; Larch and Wanner 2017; Shapiro 2021; Kortum and Weisbach 2021; Caliendo et al. 2024); trade-environment models with monopolistic competition do not directly analyze profit shifting (Nordhaus 2015; Shapiro and Walker 2018; Farrokhi and Lashkaripour 2025), though Levaggi and Panteghini (2023) provide results in a simple model of multinationals. Overviews of the trade-environment literature have little discussion of profit shifting (Copeland and Taylor 2003; Cherniwchan, Copeland, and Taylor 2017; Copeland, Shapiro, and Taylor 2022; Balboni and Shapiro 2024; Desmet and Rossi-Hansberg 2024). Optimal environmental taxation in concentrated industries differs from the Pigouvian benchmark due to market power (Buchanan 1969). A few studies analyze specific tradable industries (Fowlie, Reguant, and Ryan 2016; Ganapati, Shapiro, and Walker 2020; Hsiao 2024), without focus on profit shifting from foreign to home. Profit shifting may especially matter for trade-environment issues because polluting industries have high levels of trade exposure plus returns to scale, shipping costs, capital intensity, and other drivers of concentration (Copeland, Shapiro, and Taylor 2022; Shapiro 2024). Our analysis of the IRA's pairing of trade protection with clean subsidies connects to a broader literature emphasizing that environmental policy evaluation can usefully account for both efficiency and political economy (Zeckhauser 1981; Goulder 2020).

Finally, we contribute to the broader literature on auto market environmental regulation (Bento et al. 2009; Fowlie, Knittel, and Wolfram 2012; Jacobsen 2013; Jacobsen and Benthem 2015; Knittel and Sandler 2018). Diamond (1973) discusses the theory of homogeneous corrective taxes for heterogeneous externalities. Knittel and Sandler (2018), Jacobsen et al. (2020), Jacobsen et al. (2023), and others estimate welfare losses from imperfectly pricing heterogeneous externalities from primarily GVs. Holland et al. (2016; 2019; 2020; 2024) measure differences in EV externalities across space due to different fuels used in the electric grid. Building on their work, we incorporate market power distortions, international profit shifting, distortionary taxation, and fatal car accidents, and we analyze the social planner's problems from both global and national perspectives. These elements prove important, as distortions from market power and international profit shifting constitute a substantial portion of the constrained optimal subsidies we calculate. Our equilibrium model reflects common features of and expands on Goldberg (1995), Berry, Levinsohn, and Pakes (1999), Goldberg and Verboven (2001), Miravete, Morál, and Thurk (2018) and other work studying trade policy in oligopolistic vehicle markets by analyzing buy-lease substitution and constrained optimal subsidies. Little research compares lease versus purchase decisions, which matter since leasing accounts for a fourth of new US vehicle registrations and impacts financing markets. Our detailed dealership data and policy-induced variation in lease versus purchase prices make this an excellent setting to compare lease and purchase decisions.

Section 2 presents the policy background, Section 3 describes the data, Section 4 covers notable descriptive facts, Section 5 discusses the event studies, Section 6 introduces the structural model and welfare framework, Section 7 presents results using the structural model and analyzes counterfactuals, and Section 8 concludes.

2 Policy Background

2.1 Electric Vehicle Markets

An electric vehicle includes any vehicle with an electric motor and a plug. This covers plug-in hybrid electric vehicles (PHEVs), which have both an electric motor and a gasoline engine, and battery electric vehicles (BEVs), which lack a gasoline engine. Gasoline vehicles include any vehicles with a gasoline engine and no plug, including traditional (non-plug-in) hybrids. We exclude fuel cell vehicles since they accounted for only 0.02 percent of new vehicle sales in 2022–2023.

EVs represented 18 percent of global new light-duty vehicle sales in 2023, up from 2 percent in 2018 (IEA 2024). In 2023, about 60 percent of global new EV sales were in China, Chinese carmakers made half of all EVs sold worldwide, and China was the world's largest EV exporter (IEA 2024). China also dominates the supply chains for battery minerals and components (Leruth et al. 2022).

The Biden Administration responded to China's dominance in global EV markets by emphasizing domestic manufacturing, industrial policy, and secure supply chains. For example, Biden National Economic Council director Brian Deese said that "[we envision] a twenty-first-century American industrial strategy—a strategy to strengthen our supply chains [and] rebuild our industrial base" (Deese 2021). Similarly, Biden National Security Adviser Jake Sullivan said that "clean-energy supply chains are at risk of being weaponized in the same way as oil in the 1970s, or natural gas in Europe in 2022. So through the investments in the Inflation Reduction Act and Bipartisan Infrastructure Law, we're taking action" (Sullivan 2023). In explaining his pivotal vote for the IRA, Senator Joe Manchin (2024) wrote, "the increased risk of geopolitical uncertainty demands that we turn our focus to increasing US energy production and bringing good paying energy and manufacturing jobs back to America."

Our setting has some information about the valuation of climate damages. In regulatory analysis the US government used a global social cost of carbon (SCC) (US EPA 2023).[1]

2.2 Clean Vehicle Credits

Clean Vehicle Credits are non-refundable income tax credits of up to $7,500 for buying new plug-in EVs or fuel cell vehicles under 14,000 pounds. The Energy Improvement and Extension Act of 2008 first established EV tax credits under Internal Revenue Code Section 30D. The 2009 American Recovery and Reinvestment Act (ARRA) limited full eligibility to the first 200,000 EVs each manufacturer sold, thereafter credit amounts phased down to zero over the next four quarters. Tesla and General Motors (GM) exceeded the 200,000 limit and lost eligibility in 2018 and 2019. Toyota, Ford, BMW, and Stellantis all exceeded 200,000 by mid-2023. Thus, by mid-2023, the pre-IRA policy would have mostly subsidized purchases from foreign manufacturers, with all major domestic manufacturers of EVs being ineligible for pre-IRA credits due to reaching the cap.

Both individual and corporate taxpayers could receive the 30D credits. For example, a business could claim the credit for buying vehicles for its motor pool or for buying a vehicle to lease to an individual. In January 2024, after our data conclude, buyers became able to claim the credit at point of sale instead of waiting until they filed their taxes.

The IRA, which became law on August 16, 2022, changed 30D eligibility requirements for both taxpayers and vehicle models. For taxpayers, the IRA required that individual buyers have Adjusted Gross Income (AGI) below $300,000 for married couples filing jointly, $225,000 for household heads,

[1]The SCC represents damages to all regions, years, and pathways due to climate change. The Obama and Biden Administrations used a global SCC, while the first Trump Administration used a domestic SCC (Aldy et al. 2021) and the second Trump Administration essentially uses a SCC of zero.

or $150,000 for all other taxpayers, starting January 2023.

Figure 1 illustrates how the IRA changed eligibility of different vehicle models. The columns reflect dates of eligibility changes and the rows categorize vehicle models that jointly experience eligibility changes. The shading intensity reflects the amount of the tax credit that the models qualify for at that time, from empty (no credit) to full shading ($7,500). The first column shows that Tesla and GM vehicles received no credit pre-IRA, since they had exceeded the 200,000 vehicle sales limit (GM owns the brands Chevrolet, Cadillac, GMC, and Buick). The remaining columns reflect the dates of three changes due to the IRA.

The first major change we analyze is that starting August 17, 2022, vehicles had to undergo final assembly in North America to be eligible for credits. This excluded the European and Asian models colored red in Figure 1. We call these submodels the Excluded August 2022 group. Second, starting January 1, 2023, the policy eliminated the 200,000 vehicle sales limit, which re-included the Tesla and GM vehicles colored in blue; we call these submodels the Included Jan 2023 group. Contemporaneously, eligibility began requiring Manufacturer's Suggested Retail Prices (MSRP) below $55,000 (for cars) and $80,000 (for SUVs and trucks), which excluded the Lucid Air, Mercedes-Benz EQS, and Tesla Models S and X.

Third, beginning April 18, 2023, policy added a battery component and minerals requirement beyond the North American assembly requirement. We refer submodels thereby excluded as the Excluded/Reduced April 2023 group. This reform split the credit into two parts: $3,750 for satisfying the critical minerals requirement and another $3,750 for satisfying the battery component requirement. The critical minerals requirement stipulates that at least 40 percent of the battery minerals must be either (i) extracted or processed in the US or a country with which the US has a free trade agreement, or (ii) recycled in North America. The battery component requires that at least 50 percent of the battery components come from North America. The required percentages increased in 2024 and would have increased further in future years. In 2023, these requirements reduced or fully eliminated credits for many Ford, Jeep, Rivian, Audi, BMW, and Nissan models, colored in orange. Because substituting battery suppliers is generally infeasible in the short-run, our analysis timeframe largely excludes such substitution. Long-run analysis in future research could usefully shed light on this possible substitution.

Besides amending 30D, the IRA also established a new "Commercial Clean Vehicle Credit" under Internal Revenue Code Section 45W, effective January 1, 2023. Section 45W also offered $7,500 credits for new plug-in EVs under 14,000 pounds. All EVs qualified for 45W credits, with no final assembly, battery content, or buyer income requirements. In late December 2022, the US Treasury announced that businesses could claim the 45W credit for leasing EVs to individuals. Analysts refer to this as the "leasing loophole": individuals who would not qualify for the 30D credit to *purchase* a given vehicle, due to either vehicle eligibility restrictions or buyer income, could instead *lease* that same vehicle, and the leasing company would qualify for the 45W credit. The IRA originally specified for the 30D and 45W to sunset after 2032 and did not cap credits before then.[2] The One Big Beautiful Bill Act accelerated the credits' end to September 31, 2025.[3]

3 Data

This section describes our main data; Appendix A.1 provides further details, including on other datasets we use. Our primary dataset is a submodel-by-month panel of registrations and prices from January 2022 through December 2023 for all vehicles below 10,000 pounds. We define a "submodel" as a make $\times$ model $\times$ trim $\times$ powertrain (GV, BEV, PHEV) combination. For example, the Nissan Leaf has five submodels (S, SV, S Plus, SV Plus, and SL Plus). The four Tesla models in our data (S, X, Y, and 3) have a single trim and powertrain, so each constitute one submodel.

The registrations data come from a nationwide panel of new vehicle registrations by month and submodel that we acquired from Experian. Purchases and leases are recorded separately. We measure the lease share as the ratio of leases to total registrations. We include only registrations for personal use or lease, excluding other sales to businesses. We also exclude heavy-duty vehicles.

Our price data come from a combination of three sources, since none are complete on their own: lease terms from dealership transaction microdata from Cox Automotive, supplemental lease terms for Tesla vehicles from the Tesla website and other sources, and purchase prices from registration microdata from the California Department of Motor Vehicles (DMV).

The Cox data include purchase prices and lease terms for 6.8 million new vehicle transactions in 2022 and 2023, representing 31 percent of national transactions in those years. Brand-level coverage varies but mostly ranges from 20 to 50 percent, and state-level coverage ranges from 10 to 30 percent; see Appendix Figure A3. Cox's data coverage depends on a business relationship between Cox and the dealerships, so the data lacks new vehicle sales by direct-to-consumer brands Tesla, Rivian, and Lucid. For leases in the Cox data, we observe lease duration, annual percentage rates (APR), rebates, and monthly payments.[4] We augment the lease terms in the Cox data with Tesla lease terms for base model configurations by scraping online sources.[5]

The California DMV data covers all new vehicles registered in the state in 2022 and 2023. For purchases in the California DMV data, the reported price represents include the full price excluding sales tax, license fees, or financing costs. For leases, the California DMV data contain no information on rebates or other contract terms besides the reported price that the lease reflects. Instead of relying on them, we combine the lease terms in the Cox and Tesla data with the California purchase prices to compute lease prices that are directly comparable to observed purchase prices for all vehicles. We have also run our analyses using purchase prices from Cox for observations

[2]One writer summarized the IRA as "bottomless mimosas brunch special," since it does not limit the number of subsidies that households and firms could claim (Yablon 2023).

[3]We focus on the 2022-2023 period given our data availability. Anticipation of the expiring credits in September 2025 led to substantial EV registrations just before then.

[4]While our data record lease rebates, we suspect that rebates which are direct from the manufacturer may not be recorded, and we do not have concrete evidence on the share of rebates which are provided through this channel.

[5]See Appendix A for a description of these sources. We do not collect lease data for Rivian or Lucid submodels. Rivian does almost no leasing during this period, while Lucid only enters our sample near the end of the panel.

where they are available (approximately 93 percent of registrations in our cross-section) and found extremely similar results, as the California and Cox purchase prices have a submodel-by-month correlation of 0.99.

We construct a lease price variable for each transaction, reflecting the discounted lease payments plus the residual, i.e., the car's resale value at the lease term's end. Index transactions by i, and let $k = k(i)$ and $t = t(i)$ index the submodel and month for transaction i. Define T_i as the lease term in months. Define d_i as the down payment, m_i as the monthly payment, p_{kt} as submodel k's average purchase price, D_T as the percent depreciation over T months, and δ_t as the discount factor. We observe T_i, d_i, m_i in the Cox data, and take p_{kt} from the California DMV data. For depreciation D_T, we follow standard industry estimates that a vehicle loses 20 percent of its value in the first year and 15 percent annually thereafter (Capital One 2024). We construct the discount factor δ_t from the interest rate on new vehicle loans in month t from Federal Reserve Bank of St. Louis (2024b).[6] Let s index the series of monthly payments. The lease price equals

$$L_i = \underbrace{d_i + \sum_{s=1}^{T_i} \delta_t^{s-1} m_i}_{\text{lease payments}} + \underbrace{(1 - D_T) p_{kt}}_{\text{residual}}. \tag{1}$$

Equation (1) lets us compare lease prices to purchase prices, as both reflect a price over a vehicle's life. It also lets us compare lease prices across different lease terms.[7]

In the submodel-by-month panel, the purchase price and lease price variables represent the mean across transactions. We define a relative lease price variable equal to the submodel-by-month difference between observed purchase price and constructed lease price.

To address compositional effects from this entry, many of our analyses look at changes within submodels over time. When submodels enter or exit, many have phase-in or phase-out periods with unusually low monthly registrations. Our analysis sample excludes data from months at the beginning or end of a submodel's life, which we define as when monthly registrations fall below half of the submodel's sample average. We apply this to both EVs and GVs. Appendix Figure A5 illustrates the phase-in and phase-out periods that we exclude for EVs.[8]

Table 1 presents descriptive statistics for the submodel-by-month dataset. Our data cover 1,165 EV or GV submodels across all months. The mean submodel-by-month observation has 1,076 registrations, a purchase price of $51,140, a lease price of $48,011, and a lease share of 25 percent.

Appendix Figure A4 shows the full list of EV submodels and the months in which they appear

[6] This approach abstracts from loan-level variation in interest rates.

[7] We performed similar analyses using a simpler (though less economically founded) measure, computed as the undiscounted sums of payments while restricting to 36-month leases, the most common duration in our data. This removes the dependence on a choice of discount factors and the residual calculation. We find qualitatively similar results to those which that follow Equation (1), particularly for the response of lease prices to the 45W change in January 2023, which Figure 4 highlights.

[8] The resulting regression coefficients, which our model targets in estimation, differ by less than a percent if we do not filter on phase-in or phase-out.

in our data. We have data on a total of 62 EV submodels as of January 2022, and another 108 entered the market between January 2022 and December 2023.[9]

In addition to the submodel-by-month panel, we use several other types of data. First, to measure supply chain constraints, we use monthly "days-to-turn" from Edmunds (2024), i.e., the mean duration that vehicles sold in that month were available in the dealership's inventory before being sold. The Edmunds data exclude Tesla, so we collect delivery wait times originally reported on the Tesla website (Tesla 2023; Pritchard 2023; The Internet Archive 2023).

Second, in summer 2023, we surveyed dealerships to determine EV market wait times, prices, and other market conditions. Research assistants collected data on the earliest date they could drive home popular EV models. This survey obtained 681 data points from 258 dealerships in each of eight metro areas and 20 brands, excluding Tesla and Rivian. These interviews guide our discussions of evolving supply chain conditions throughout 2022-2023 and lead the equilibrium model to focus on summer 2023 as a baseline. Appendix A.3 describes the survey in detail.

Third, to identify substitution patterns in our demand model, we use second choice data from the New Vehicle Experience Survey (NVES), administered by the company Strategic Vision. Strategic Vision surveys a large sample of US new vehicle buyers soon after their purchase or lease, and has a response rate of about five percent. Among other questions, the survey asks whether the buyers considered any vehicles other than the one they purchased or leased, and if so what model. The survey also asks for their household income. We have 339,560 survey responses from the respondents who acquired a new vehicle in 2022 and 2023.

Fourth, we use a few data sources to measure how changes in EV markets affect domestic auto industry employment, EV battery assembly, and EV plant investment. We calculate these effects by combining our model-implied marginal cost estimates, the US input-output table, and wage data together with assumptions grounded in prior work of the cost breakdown between parts and final assembly; Appendix A.4 provides details.

Finally, we use several sources to measure externalities; Appendix A.2 provides details. Our main analysis assumes that vehicles impose four externalities: CO_2 emissions from manufacturing and scrap, CO_2 and local air pollution emissions from driving, fatal accidents, and fiscal externalities from explicit or implicit taxes on gasoline and electricity. For CO_2 emissions from the value chain of manufacturing plus scrapping vehicles, we use estimates from Argonne National Labs (Kelly et al. 2022), which distinguishes three powertrains (BEV, PHEV, GV). We rescale emissions from the manufacturing of EV batteries by the size of each submodel's battery. For CO_2 emissions and local air pollution damages from driving vehicles, we combine estimates of local air pollution damages and local grid emission intensities from Holland et al. (2024) with US EPA (2024a) exhaust test and fuel efficiency records. We assume that 63 percent of PHEV miles traveled are on gasoline and 37 percent are on electricity, following Plötz et al. (2020). Motivated by the fact that EVs are capable

[9]Timing makes it unlikely that the IRA's passage affected the introduction of new models in 2023, for two reasons. Model planning typically requires multiple years' lead time. Additionally, in 2021 and up through August 2022, auto manufacturers faced substantial uncertainty about the likelihood of the IRA's passage or the details of EV tax credits conditional on IRA passage.

of benefiting from future improvements in grid emissions intensity, we conduct a sensitivity analysis using long-run marginal emissions estimates from the National Renewable Energy Laboratory to estimate damages from EV charging. which reduces estimated EV environmental damages relative to our baseline assumptions. For the mortality cost of car accidents due to each submodel's weight relative to the lightest vehicle, we use regression estimates from Anderson and Auffhammer (2014) and apply the US Department of Transportation (2024) \$13.2 million value of a statistical life. For positive fiscal externalities, we use the utility-specific markups on residential electricity above private marginal cost calculated by Borenstein and Bushnell (2022) for EVs, as well as federal and state gas taxes for GVs. For all externalities, we assume that vehicles have a useful life of 150,000 miles, following US EPA (2014).[10] We inflate all values to July-August 2023 dollars using the CPI for Urban Consumers (Federal Reserve Bank of St. Louis 2024a). Our main analysis assumes that externalities including marginal damages do not change over time in real terms, so we do not discount externalities from driving later in a vehicle's life.

We assume a global social cost of carbon of \$241 (in July-August 2023 dollars), following US EPA (2023). The "domestic SCC" uses domestic (instead of global) damages from CO_2 emissions, equal to \$28 per ton, computed using the ratio of the US SCC to global SCC from Ricke et al. (2018) times our CPI-inflated global SCC.

Our use of the domestic versus global SCC values deserves additional discussion. The domestic SCC describes the damages to a country resulting from an additional ton of CO_2. Using the global SCC for policy design may generate larger environmental benefits than using the domestic SCC, since cooperative use of the global SCC efficiently addresses cross-border externalities (Barrett 1994; Weitzman 2014; Kotchen 2018). In other words, since the setting of climate policy is a repeated game with strategic interactions across countries, the domestic SCC represents a figure that is likely lower than the optimal carbon tax for a planner focused only on US welfare. In welfare aggregation and quantification, we use the domestic SCC to report domestic costs of CO_2 emissions and the global SCC to report global costs of CO_2 emissions. This allows us to decompose the share of global benefits of CO_2 mitigation accruing between the US and foreign countries. We also separately report how each counterfactual affects quantities of CO_2, which can be evaluated using any SCC of interest. We view this measurement decision as distinct from the normative decision about whether a country ought to design policy using the domestic or foreign SCC.

4 Descriptive Facts

Several descriptive facts play important roles in developing and interpreting our empirical results. To address compositional effects from submodel entry and market share changes, many of our descriptive figures using the submodel-by-month dataset present fixed-weight arithmetic indices.

[10] Available evidence is limited though supports our assumption that EVs and GVs have a comparable useful lifetimes. Nguyen-Tien et al. (2024) estimate a survival model of 30 million vehicles registered in Great Britain. Their preferred specification indicates that the median lifetime of BEVs in years is 1.5 percent below the median lifetime of GVs, and that the median lifetime miles for BEVs are about 7.5 percent greater than for GVs.

Specifically, for a variable such as prices, we first compute the mean for a group of submodels in January 2023, weighting submodels by mean monthly sales in months when the submodel was available (the "fixed-weight"). For each previous or subsequent month, we then recursively add the sales-weighted mean change for all submodels available in both months to produce the index (see Appendix A.1). This prevents the series from displaying fluctuations entirely driven by panel imbalance.

Tesla has dominated the US EV market. Panel (a) of Figure A1 presents registrations by month, separately for Tesla and other EVs. Tesla represents 53 percent of US EV sales in 2022 and 2023. Thus, Tesla plays an important role in our event study estimates and counterfactuals. After our sample years, Tesla's market share fell below 50 percent in 2024 and 2025.

EV prices peaked in mid-2022. Panel (b) of Figure A1 presents fixed-weight indexes of vehicle prices by month. EV prices increased in early 2022, peaked in mid-2022, and decreased steadily thereafter. Tesla initiated the price cuts at the end of 2022 and other manufacturers soon followed. Media reports attribute the price cuts to the improvement of pandemic-related supply chain bottlenecks plus softening demand partly due to interest rate hikes (Boudette 2023; Cao 2023; Shepardson and Nair 2023).

Inventory constraints peaked in mid-2022. Figure 2 presents evidence of supply constraints related to the price trends. Panel (a) presents the fixed-weight index of days-to-turn for GVs and EVs, excluding Tesla. The average non-Tesla EV sold in July 2022 had sat at the dealership for about 20 days, while the mean vehicle sold in July 2023 had been at the dealership for over 50 days. Days-to-turn of 15 to 20 may be near just-in-time sales for a typical car, while days-to-turn of 50 represents less severe supply chain constraints.[11] Panel (b) presents the fixed-weight index of delivery wait time for Tesla models. The mean Tesla ordered in July 2022 would be delivered in about 200 days, while, one year later, the mean Tesla ordered in July 2023 would be delivered in about 25 days. Our dealership survey found that by summer 2023, market share-weighted EV wait times were below one month for 94 percent of EVs sold via dealerships and 90 percent of EVs were available immediately. Guided by these patterns, our event study analyses in Section 5 consider the relevance of supply constraints for the August 2022 change in tax credit eligibility. We interpret the April 2023 change in eligibility as facing less severe supply chain constraints. Additionally, this evidence informs the choice to base our equilibrium model in Section 6 around July–August 2023, when supply chain conditions had eased.

A majority of EV buyers have incomes below the eligibility limit. The IRA's Section 30D credits required buyers to have incomes below the $300,000 for married couples filing jointly, $225,000 for household heads, or $150,000 for all other taxpayers. The NVES data show that 57 percent of EV buyers in 2022 and 2023 reported household income below $200,000, and 78 percent reported household income below $300,000; see Appendix Figure A6. The IRS Statistics of Income (SOI) data show that 54 percent of taxpayers who claimed 30D credits in 2021 had Adjusted Gross

[11]For reference, our full data show the average days-to-turn was above 50 for both powertrains all throughout 2019 and 2020, only dipping below this threshold in the supply-constrained period of 2021 and 2022.

Income under $200,000. Our equilibrium model accounts for income eligibility and how income affects EV demand.

Assembly locations shifted little after the 30D eligibility requirement. Most vehicles excluded from eligibility did not change their assembly sites in our analysis timeframe.[12] This guides our interpretation and focus of our analysis on the short- to medium-run, which we interpret as a period of largely fixed international sourcing.

The EV market share was growing but the domestic assembly share was not. Panel (a) of Figure A2 shows that the EV share of new vehicles rose from 6.9 percent in the first quarter of 2022 to 12 percent in the fourth quarter of 2023. Panel (b) shows that the share of EVs produced in the US stayed roughly constant at around 70 percent over this same period. Of course, this graph does not show what would have happened absent the IRA—these trends resulted from the IRA credits plus ongoing market forces. For example, foreign manufacturers introduced a disproportionate number of new EV submodels from late 2022, likely independently of the IRA, since submodel introduction involves a several year lead time. Even without the IRA, this introduction might have decreased the North American assembly share of EVs in the time series.

The EV credits largely represent a "Buy American" policy. Panel (b) of Figure A2 shows that about 90 percent of EVs assembled in North America are US-assembled. The share of North American-assembled GVs that are US-assembled is much lower, at about two-thirds. While the Section 30D EV credits required North American assembly, these data show that in practice, in the short-run, this required US assembly, leading us to interpret this setting as more "Buy American" than "Buy North American."

Dealers advertise and respond to EV subsidies. Many dealerships in our survey mentioned the EV credits. Many dealerships also undertook advertising campaigns highlighting $7,500 rebates on leases; Appendix Figure A7 provides one example. Several dealers in our survey also proposed a strategic transaction to evade Section 30D restrictions—first a customer leases the vehicle, then soon afterwards the customer would buy out the lease. This would obtain the $7,500 Section 45W leasing credit for what was effectively a purchase, without facing trade, income or MSRP restrictions. Discussions of the EV leasing market in 2023 mentioned this "loophole within a loophole" (Davis 2023; Bernstein 2024). We investigated the statistical prevalence of this strategic evasion in the Texas registration data, where we are able to track vehicles over time. We estimate that it exists but is quite rare; see Appendix B.1.

EVs have somewhat lower externalities than GVs. Table 2 summarizes lifetime submodel-level externality values by powertrain. Using the global SCC, the mean EV imposes about $14,000 in lifetime negative externalities, while the mean GV imposes $19,300 in negative externalities. It may be surprising that the difference between EVs and GVs is not larger. The table rows show that

[12] A notable exception is the Volkswagen ID.4, which transitioned assembly from Germany to Volkswagen's Chattanooga, Tennessee plant, though this shift began before the IRA's passage. Hyundai, Kia, and Nissan also announced and begun constructing US facilities for their EVs around this time. Hyundai's investment in Georgia was announced before the IRA; Kia's Georgia facility was announced in mid-2023. Both began production by 2025. Nissan's announcement had 2026 as the target date for production, but later postponed to 2028.

while EVs do have \$6,600 lower CO_2 externalities from driving, they have higher other non-fiscal externalities—higher CO_2 externalities from manufacturing (\$1,200), slightly higher local pollution externalities via the electric grid (\$200), and higher accident externalities due to EVs' greater weight (\$2,200), though this is offset by more positive fiscal externalities (\$2,200).

This partially reflects composition within EVs between BEVs and PHEVs. Unlike BEVs, on average, PHEVs have CO_2 externalities only marginally lower than those of GVs. They also have \$3,000 higher accident externalities than GVs, and \$1,000 higher accident externalities than BEVs, due to their greater weight. How much this contributes to the total externality difference with GVs depends on the chosen SCC. Under the global SCC, PHEVs have similar negative externalities to GVs under, but PHEVs have *higher* average externalities under the domestic SCC, which places less value on their lower CO_2 emissions.

Table 2 also shows that environmental externalities from CO_2 exceed environmental externalities from local air pollution, which also occurs under the domestic SCC. For this reason, while our analysis measures both sets of externalities, our subsequent discussions of the "environment" primarily reflect CO_2.

We note that EVs and GVs have different makeups across vehicle classes. For example, 40 percent of EVs are large luxury vehicles, compared to 24 percent of GVs.[13] EVs, like some other innovative technologies, entered the market at higher prices and are gradually reaching a broader customer base. At the same time, short- to medium-run changes to EV subsidy policy may especially affect market shares for the classes of vehicles already in the market. Thus, our comparisons of EV and GV externalities reflect differences in these powertrains' attributes during our period of analysis. We conjecture that in the long run, EVs may move towards a more similar distribution across vehicle classes as GVs.

EVs have large heterogeneity in externalities and similar heterogeneity as GVs. Figure 3 visualizes the substantial variation in externalities across EV submodels, which reflects their different weights and electricity use per mile. For both EVs and GVs, valued at the global SCC, most vehicles have externalities of \$5,000 to \$30,000, while valued at the domestic SCC, most vehicles have externalities of \$0 to \$15,000. Dispersion is similar within EVs as within GVs. For example, the 90th percentile submodel among EVs generates externalities of \$22,600 over its lifetime, while the 10th percentile submodel among EVs generates \$10,000 in externalities; the comparable statistics for GVs are \$27,200 and \$14,200. We also note one other type of heterogeneity: the mostly foreign-assembled vehicles that the 30D credits exclude have slightly larger negative externalities than 30D-eligible submodels (\$833 on average), which affects our evaluation of trade restrictions in Section 6.[14]

[13]These statistics use data from the Wards Automotive Yearbook for 2022, which is available at model level, so these represent the share of models but not registrations (Wards Intelligence 2022). We define large luxury vehicles using the provided Wards segmentation as any Luxury Sport/Utility or Luxury Cross/Utility vehicle.

[14]This largely reflects Tesla. Excluding Tesla and comparing only 30D-eligible to ineligible EVs reverses the sign. Teslas have lower externalities than the average EV both because they are BEVs rather than PHEVs and because the Tesla Model 3, the most popular EV sedan, is smaller and lighter than the typical EV, many of which are crossovers or SUVs.

Table 3 shows two measures of the dispersion in externalities across submodels—the coefficient of variation, which equals the standard deviation divided by the mean; and the interdecile ratio, which equals the log of the 90th percentile externality divided by the log of the 10th percentile externality. This table shows the surprising result that EVs and GVs have broadly similar dispersion in externalities, driven in part by the variation within EVs across BEVs and PHEVs. Tests fail to reject that dispersion is equal for the two powertrains. This finding also applies for total externalities when separately comparing BEVs and PHEVs to GVs, as well as to several components of externalities individually.

The standard deviation of carbon damages across EV submodels is just under twice the standard deviation of carbon damages across states, averaging across EV submodels (Holland et al. 2016). Geographically, the least carbon-intensive region has approximately half the carbon emissions per kWh of the most carbon-intensive region; across vehicles, the most carbon-intensive submodels have over three times the carbon damages per mile as the least carbon-intensive submodels.

The finding that EVs and GVs have similar dispersion in externalities matters because many policies globally move consumers from GVs to EVs ("vehicle electrification"). Such policies largely ignore whether consumers purchase high- or low-externality EVs. Policies that make consumers substitute from low-externality GVs to high-externality EVs (e.g., Priuses to Cybertrucks) can increase externalities. Our results show that EV policies may benefit from encouraging substitution from high- to low-externality EVs, just as many GV policies encourage substitution from dirty to clean GVs. Additionally, policies like the IRA that subsidize some but not all EVs could inadvertently increase emissions if they subsidize dirty EVs. The counterfactual analysis in Section 7 revisits these ideas.

5 Event Studies Around Credit Eligibility Changes

This section uses event study analyses that exploit variation over time in eligibility for the EV credits to estimate effects of the EV credits.

5.1 Methodology

Our event study analyses focus on lease shares and to a lesser extent prices. Estimates for registration quantities were potentially more related to supply conditions and other market trends; see Appendix C.3. We present two graphical analyses: descriptive trends in the fixed-weight index and event study estimates (the event studies use actual values, not the index). The event studies use two-way fixed effects regressions with GVs as controls. In equilibrium, policy changes for any vehicle can affect all vehicles, so the event study estimates capture changes relative to controls, not absolute effects against an unaffected control group.

To formalize the methodology, define y_{kt} as the lease share for submodel k in month t. We index tax credit eligibility groups by $e = e(k)$ and define t^e as the month when group e's eligibility changes. We let s index months in event time (relative to t^e), and we define $\mathcal{S}^e$ as the set of months in event time over the 24-month sample, excluding month $s = -1$. Let D_k represent an indicator for whether submodel k experienced an eligibility change.[15] We define ϕ_k and ν_t as submodel and month-of-sample fixed effects. We estimate event study graphs using

$$y_{kt} = \sum_e \sum_{s \in \mathcal{S}^e} \gamma_s^e D_k \cdot 1\{t - s = t^e\} + \phi_k + \nu_t + \varepsilon_{kt}. \tag{2}$$

We cluster standard errors by submodel to account for correlation across submodels and over time. As in the descriptive figures, we weight all observations of submodel k by the mean monthly registrations in the months when this submodel is available. Unweighted results would be sensitive to idiosyncratic outcomes for low-volume submodels and to the exact definition of a submodel.

We focus on the evolution of outcomes within four groups groups of EVs. The "Excluded August 2022" group covers vehicles eligible under pre-IRA policy but ineligible as of August 2022 due to assembly outside of North America,. The "Included January 2023" group covers Tesla and GM EVs, which lost credit eligibility under pre-IRA policy due to exceeding the 200,000 sales cap but then became eligible for lease credits and mostly eligible for 30D purchase credits in January 2023.[16] The "Excluded/reduced April 2023" group includes vehicles which were initially eligible for 30D purchase tax credits under the IRA but then lost half or all of the purchase credits due to battery sourcing requirements. Finally, the "Other EVs" group had no or other eligibility changes (i.e., they were always eligible, never eligible, or newly excluded in January 2023 due to MSRP caps). In some cases, such as our analysis of the impact of changes to the 45W lease credit, we include the vehicles with an eligibility change in April 2023 in the "Other EVs" group.

We considered several alternative specifications. "Doubly robust" specifications where the GV control group is reweighted to match the EV pre-IRA average price give similar estimates; see Appendix C.2. Alternative specifications using only EVs as controls give considerably noisier estimates that are mostly not statistically distinguishable.[17]

5.2 Prices and Economic Incidence

This subsection discusses purchase prices around 30D tax credit eligibility changes. These results provide some evidence on the economic incidence of the credits, with the strong caveat that trends unrelated to the IRA in the new vehicle (and especially new EV) market over the period we study, including a serious supply crunch due to computer chip shortages and other supply chain constraints, affect our price event study analyses. Additionally, the pass-through that our estimates capture are local to consumers who continue to purchase while many substitute to leasing (see Figure 5).

[15] When considering purchase prices and registrations, we replace D_k with the absolute value of the change in purchase credit available to submodel k, divided by \$7,500. For example, a vehicle that becomes eligible for the full \$7,500 tax credit has $D_k = 1$, and a vehicle where eligibility falls from \$7,500 to \$3,750 has $D_k = 0.5$. This primarily affects the vehicles which experienced a partial reduction in credit eligibility in April 2023.

[16] The upmarket Tesla Models S and X were the two exceptions that did not gain eligibility.

[17] New difference-in-difference approaches that focus on addressing staggered treatment timing (Roth et al. 2023; Roth 2024), are less relevant in our setting because equation (2) estimates a separate set of coefficients $\{\gamma_s^e\}$ for each eligibility group.

Furthermore, ineligibility of some households (Figure A6) and the non-refundability of tax credits may decrease takeup. In our setting, constant purchase prices around an eligibility change would correspond with consumers bearing the full economic incidence, up to the complications of market trends beyond the policy change. This is because, during our analysis period, buyers can later claim the 30D tax credit on their individual income taxes.

Appendix C.3 presents and discusses results. Overall, the data show modest change in transaction prices when vehicles lose credit eligibility. While this is what would occur if consumer obtained much of the economic incidence of these credits, the potential relevance of market-wide trends and constrained supply conditions leads us to discuss those estimates cautiously.

We also study lease prices as a measure of economic incidence on consumers choosing to lease. Our empirical analyses focus on the relative lease price (i.e., lease price minus purchase price) for each submodel-by-month observation, to difference out potentially confounding pricing trends.[18]

Before and after the IRA, Section 30D allowed firms that lease vehicles to claim corporate income tax credits for leasing eligible vehicles to any buyer. Thus, firms leasing vehicles in the Excluded August 2022 group could claim credits under 30D through August, 2022, lost eligibility from August to December, and could again claim credits under 45W beginning January, 2023. Tesla and GM could not claim tax credits for leasing in 2022 and the several preceding years, but they could claim credits under 45W (or 30D, for eligible models) starting January 1, 2023. Firms leasing all other vehicles could always claim tax credits for leasing EVs.

The lease tax credit effectively reduces the seller's marginal costs for leasing a vehicle relative to selling it. In a Nash-Bertrand pricing model like Section 6 describes, if leasing and purchasing the firm's other vehicles experience approximately proportional cross-price effects, one would expect that newly eligible firms would reduce the price of leasing relative to purchasing by roughly $7,500, the amount of the tax credit.

Appendix C.3 presents and discusses event study estimates for relative lease prices. Overall, relative lease prices declined by $5,000 or more as the leasing loophole made leasing more attractive.

5.3 Lease Shares

Purchase-to-lease substitution is an important facet of the leasing loophole's effects. If many consumers are willing to lease instead of purchase, then the leasing loophole can have large effects. If few consumers substitute towards leasing, then the leasing loophole will have limited effects.

One might expect an increase in EV lease shares in 2023 for two reasons. First, a price effect—as the previous subsection discusses, relative lease prices decreased for some EVs in 2023. Second, a buyer eligibility effect—when the new Section 30D buyer income limits constrained eligibility in January 2023, the relative price of purchasing 30D-eligible vehicles increased for income-ineligible buyers.

Panel (a) of Figure 5 presents the fixed-weight indexes of lease shares for the same three groups

[18] We estimated qualitatively similar and slightly larger effects when these analyses were conducted on lease prices in levels.

plotted in Figure 4. For the Included Jan 2023 group, the lease share is about 10 percent until the end of 2023, matching the timing of Tesla's lease rebates. For both the Excluded August 2022 group and all other EVs, lease shares decreased moderately in 2022 and then increased markedly in the first half of 2023. Figure A9 provides a complementary descriptive figure, and shows trends in lease shares for EVs eligible and ineligible for the purchase credit within the NVES data, split by household income eligibility.

Panel (b) of Figure 5 presents the corresponding event study estimates, where we again define the "event" as occuring in January 2023. Consistent with Panel (a), we see a 40 to 45 percentage point lease share increase for the Excluded August 2022 group compared to the GV trend since December 2022, little change for the Included January 2023 group until the end of 2023, and a 20 to 30 percentage point increase for all other EVs.

These substantial leasing increases blunt the impact of the Section 30D trade and income restrictions and reflect some deadweight loss, as tax incentives induce leasing by consumers who would not have otherwise leased. They also guide our equilibrium model, which treats leasing and purchasing as separate options.

6 Equilibrium Model

6.1 Model Setup

Demand We assume a demand system with heterogeneous types corresponding to income levels. Within each type, we describe a continuum of consumers with idiosyncratic preferences according to a four-level nested logit demand system. The nests capture four margins of substitution that are relevant for evaluating EV purchase and lease credits: between purchases and leases of the same submodel, across submodels within a vehicle class, across vehicle classes within a powertrain, and from EVs to GVs. Incorporating income allows us to model the household income restrictions to credit eligibility. It also allows us to match other realistic purchasing patterns in the market—how average vehicle price and the likelihood of acquiring a new vehicle, an EV, and a lease vary across the income distribution. In addition, recent work has shown that demographic interactions are important to generate a demand system that is flexible enough to allow for a range of pass-throughs (Miravete, Seim, and Thurk 2023).

Consumers have quasilinear utility and unit demand, so they select exactly one good plus a continuous amount of the numeraire. Consumers choose between submodels and transaction types (purchase or lease). Consumers can purchase any submodel and can lease most submodels, if it offers a lease option. We index each submodel-by-transaction type choice by j. Each choice corresponds to a submodel $k(j)$, class $c(j)$, and gasoline or electric powertrain $g(j)$. We define class as a combination of vehicle segment (e.g., sedan, SUV, etc.) and powertrain, so an EV sedan is a different class than a GV sedan.[19] There are J total inside goods, plus we include $j = 0$ to index

[19]Our data have nine classes with enough registrations to include in estimation. GVs include SUVs, sedans, pickup trucks, minivans, and coupes/convertibles. EVs include SUVs, sedans, pickup trucks, and minivans. Informed by the

the outside option (e.g., buying a used vehicle).

The market has M consumers, indexed by i. Consumer i belongs to one of a finite set of consumer types $h(i)$, with population shares w_h. Each consumer selects the choice j that maximizes their utility. Let $y_{h(i)}$ be the representative income of consumer i, let p_j represent the purchase price or lease price, and let $\tau_{h(i)j}$ be the available 30D tax credit accounting for income eligibility. Indirect utility from choice j is given by

$$U_{ih(i)j} = \xi_j - \alpha_{h(i)} \left(p_j - \tau_{h(i)j}\right) + \boldsymbol{\beta}'_{h(i)} \boldsymbol{X}_j + \epsilon_{ij}. \tag{3}$$

Here, $\alpha_{h(i)}$ represents the marginal utility of money and $\boldsymbol{\beta}_{h(i)}$ represents heterogenous preferences for specific vehicle characteristics in $\boldsymbol{X}_j$. Common preferences for vehicle and purchase option attributes are captured by ξ_j. Finally, ϵ_{ij} is an idiosyncratic preference distributed type-1 extreme value, which we discuss below. We normalize $U_{ih(i)0} = \epsilon_{i0}$ for the outside option. Bold indicates vectors, so $\boldsymbol{\xi}$ is the vector of ξ_j parameters, and $\boldsymbol{X}_j$ is a vector of binary inside good indicators, binary EV indicators, and binary lease indicators.

We allow ξ_j to differ freely between the purchase and lease option of the same submodel. While the physical vehicle is the same between these choices, contract-specific differences determine the attractiveness of leasing relative to purchasing. Manufacturers push specific lease incentives, calculate residual values, decide whether to allow lease buyouts, and provide financing terms that vary by submodel. Consumers may therefore perceive the relative value of leasing differently across submodels.

We parameterize heterogeneous preferences across types by

$$\boldsymbol{\beta}'_{h(i)} \boldsymbol{X}_j = (\beta_0 \times 1_j\{\text{Inside good}\} + \beta_{EV} \times 1_j\{\text{EV}\} + \beta_{Lease} \times 1_j\{\text{Lease}\}) \times y_{h(i)}.$$

We parameterize price sensitivity across types by

$$\alpha_{h(i)} = \exp\left(\alpha_0 + \alpha_y y_{h(i)}\right),$$

which maintains the property that demand is downward-sloping. Here, $\alpha_y < 0$ would imply that low-income households are more price elastic.

We assume a nested logit error structure for ϵ_{ij}. Appendix Figure A15 shows the nesting structure. The nested logit model differs from a standard multinomial logit by allowing the idiosyncratic error to be correlated across vehicles that share a nest. Specifically, we define three sets of random coefficients $\left\{\zeta^k_{ik(j)}, \zeta^c_{ic(j)}, \zeta^g_{ig(j)}\right\}$ representing idiosyncratic preferences common to all choices within a group. For example, $\zeta^g_{i,GV}$ represents a random coefficient common to all choices within GVs. This commonality generates correlation in preferences across choices. Three parameters

patterns in the second choice surveys, we combine hatchback vehicles with sedans and crossover vehicles with SUVs. The options for second choices available to survey respondents partially aggregate across trims, and in rare instances aggregate the EV version of a vehicle with its GV counterpart; we treat these as a GV second choice. Minivans are the primary example of this, since no EV-only second choice is present in the survey. Since EV minivans have a tiny market presence and we weight by first choice shares, this minimally affects our estimates.

$\{\sigma^k, \sigma^c, \sigma^g\} \in [0,1)$ capture the dispersion of these sets of random coefficients.[20] Then ϵ_{ij} takes a standard nested logit form:

$$\epsilon_{ij} = \zeta^g_{ig(j)} + (1-\sigma^g)\,\zeta^c_{ic(j)} + (1-\sigma^g)(1-\sigma^c)\,\zeta^k_{ik(j)} + (1-\sigma^g)(1-\sigma^c)\left(1-\sigma^k\right)\tilde{\epsilon}_{ij}, \tag{4}$$

where $\tilde{\epsilon}_{ij}$ is i.i.d. type-1 extreme value, uncorrelated across j. To be consistent with random utility maximization, we require $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$ (McFadden 1978). If $\sigma^k = \sigma^c = \sigma^g = 0$, this reduces to standard logit. As the dispersion parameters approach 1, the within-nest preference correlation increases, making consumers more likely to select alternatives that share a nest.

Concretely, consider a consumer whose first choice is purchasing an EV sedan submodel. A larger σ^k implies more probable substitution to a lease of the same submodel than to a different submodel, a larger σ^c implies more probable substitution to another vehicle of the same class than to a different class, and a larger σ^g implies more probable substitution to another EV than to a GV or to the outside option.

The market share for any choice among each type, s^h_j, and the aggregate market demand summing over types, q_j, is given by

$$\begin{aligned} s^h_j &= \int 1\left\{U_{ihj} \geq \max_{k=0,\dots,J} U_{ihk}\right\} dF(\boldsymbol{\epsilon}_i) \\ q_j &= M \sum_h w_h s^h_j. \end{aligned} \tag{5}$$

We provide specific functional forms under the nested logit assumption in Appendix D.1. The substitution between any two choices j and r can be compactly expressed in terms of conditional choice shares within nests for each type. Writing the market share in equation (5) as the product of conditional shares via $s^h_j = s^h_{j|k(j)} s^h_{k(j)|c(j)} s^h_{c(j)|g(j)} s^h_{g(j)}$ (where, for example, $s^h_{c(j)|g(j)}$ represents the conditional market share of choice j's class within its powertrain $g(j)$ among consumers of type h) delivers

$$\begin{aligned} \frac{\partial q_j}{\partial p_r} = M \sum_h w_h \alpha_h s^h_j \Bigg[& s^h_r + \left(\frac{1}{1-\sigma^g} - 1\right) s^h_{r|g(j)} 1\{g(j) = g(r)\} \\ & + \left(\frac{1}{1-\sigma^c} - \frac{1}{1-\sigma^g}\right) s^h_{r|c(j)} 1\{c(j) = c(r)\} \\ & + \left(\frac{1}{1-\sigma^k} - \frac{1}{1-\sigma^c}\right) s^h_{r|k(j)} 1\{k(j) = k(r)\} \\ & - \left(\frac{1}{1-\sigma^k}\right) 1\{j = r\} \Bigg] \end{aligned} \tag{6}$$

[20] Cardell (1997) and Galichon (2022) study this formulation of the nested logit model. Galichon (2022) derives the exact structure of the correlation across choices using the representation in equation (4). In our setup, for any two choices j and r, $\mathrm{Cor}(\varepsilon_{ij}, \varepsilon_{ir}) = 1 - \left[(1-\sigma_g)^{\delta_{g(j),g(r)}}(1-\sigma_c)^{\delta_{c(j),k(r)}}(1-\sigma_k)^{\delta_{k(j),k(r)}}\right]^2$, where $\delta_{a,b}$ is the Kronecker delta.

Equation (6) shows how, when $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$, we see increasing substitutability between two different choices ($j \neq r$) that share a nest, since each term in the expression will be positive and there are more indicator terms as products share more nests . By contrast, the own-price substitution ($j = r$) will be negative due to the final subtracted term.

Supply Auto manufacturing firms indexed by f each offer submodel-by-transaction type choices among their portfolio $\mathcal{J}_f$. Firms set their prices to maximize surplus in static Nash-Bertrand competition.[21] The terms $\boldsymbol{p}$ and $\boldsymbol{\tau}$ represent the vectors of prices and 30D credits faced by consumers for all choices, c_j is marginal cost, and κ_j represents the 45W credit available to firms for leasing choice j. In practice, c_j could be interpreted as marginal *opportunity* cost, which could include both physical production costs and cost reductions due to the dynamic benefits from learning-by-doing as in Barwick et al. (2025). The function $q_j\left(p; \boldsymbol{p}_{-j}, \boldsymbol{\tau}\right)$ represents choice j's total quantity demanded from equation (5) as a function of its price, given the price of all other products in the market and demand subsidies available. Firm f then solves the following maximization problem for all products in its portfolio:

$$\max_{\{p_j\}_{j\in\mathcal{J}_f}} \sum_{j\in\mathcal{J}_f} (p_j - c_j + \kappa_j) \times q_j\left(p_j; \boldsymbol{p}_{-j}, \boldsymbol{\tau}\right), \tag{7}$$

where $(p_j - c_j + \kappa_j)$ is the 45W credit-inclusive markup over marginal costs, which we will denote using μ_j when computing producer surplus.[22] Firm f's first-order condition with respect to an arbitrary choice j in $\mathcal{J}_f$ is

$$[p_j]: \quad q_j + \sum_{r\in\mathcal{J}_f} (p_r - c_r + \kappa_r) \frac{\partial q_r}{\partial p_j} = 0. \tag{8}$$

We define firms f at the level of the parent company, such as Stellantis (which owns Chrysler, Dodge, Jeep, and other brands). Our data have 17 firms.

Equilibrium The equilibrium describes a set of prices $\boldsymbol{p}$ such that any firm f facing demand for their products as in equation (5) and taking prices of competitor firms as given has, for each j in its portfolio, a best response p_j that satisfies equation (8) in the pricing game and is consistent

[21] We assume no interactions with the federal fuel economy and greenhouse gas emission standards. Automakers had many banked of compliance credits in 2023, though many transacted over the period we study (US EPA 2024b). The standards did not bind for that year at the industry level, but were designed to generally bind over a longer future period. Our assumption would exactly reflect reality if a future administration set non-binding standards or set future stringency to equate marginal benefits and marginal costs of future compliance. This occurred under the second Trump administration, which substantially weakened these standards (Domonoske 2025). Our setting would violate this assumption if more EV sales in 2023 make it easier to comply with the standards in future years. This would generate a "waterbed effect," through which EV tax credits would have smaller net effects on CO_2 emissions.

[22] For robustness, we consider an alternative conduct assumption where all EV manufacturers except Tesla price EVs at zero marginal cost (i.e., no markups). This "penetration pricing" check reflects a scenario where manufacturers seek to maximize production subject to nonnegative profits, which can increase dynamic benefits in a setting with learning-by-doing through production. One implication is that EV credits to these firms are fully passed through to consumers and the primary market inefficiency comes from externalities, rather than market power for most EVs (Tesla and GVs do retain market power). Appendix Table A6 presents those results.

with the price vector $\boldsymbol{p}$. Nocke and Schutz (2018) show that a unique price equilibrium under Nash-Bertrand competition exists with nested logit demand and multi-product firms whenever each firm supplies products only in one of the nests. Garrido (2024) extends this uniqueness result to a nested logit with deeper nesting structures, but demonstrates that it no longer holds under consumer heterogeneity—observed or otherwise. This is the same difficulty in establishing unique pricing equilibria that consumer heterogeneity introduces into mixed logit demand models with multi-product firms, even absent any nesting. On this front, imposing downward-sloping demand, as we do, is often helpful. Still, our baseline model does not guarantee these sufficient conditions for uniqueness along both dimensions: the ownership structure on the supply side and consumer heterogeneity on the demand side. However, in practice we do not encounter multiple equilibria in estimation.

Still, for robustness, we consider two related specifications. The first is a version with no consumer heterogeneity in which each firm separately prices its products within each powertrain-class nest, not taking into account within-firm cannibalization across powertrain-class nests. This model of demand satisfies Nocke and Schutz (2018)'s conditions for uniqueness. This specification has less variation in markups across products within a firm and lower markups overall. The share-weighted correlation in markups has reasonable magnitude, at 73 percent. The second specification replaces preserves consumer heterogeneity but replaces the nine powertrain-by-class nests with four powertrain-by-foreign/domestic brand nests. This version has a substantially different ownership structure across nests than the baseline model, but the share-weighted correlation in markups is 98 percent. This gives one additional confidence that the baseline model is not encountering a particular, distant local equilibrium and that our results are not overly sensitive to the definition of product ownership.

6.2 Estimation Procedure, Calibration, and Results

This subsection describes our estimation procedures, targeted moments, and evaluation of model fit. Appendix D.2 provides additional details.

We estimate the following sets of parameters: the J-vector of non-price attributes $\boldsymbol{\xi}$; the two price response parameters $\boldsymbol{\alpha} = \{\alpha_0, \alpha_y\}$, three preference parameters $\boldsymbol{\beta} = \{\beta_0, \beta_{EV}, \beta_{Lease}\}$, and three nested logit parameters $\sigma = \left\{\sigma^k, \sigma^c, \sigma^g\right\}$; and the J-vector of marginal costs $\boldsymbol{c}$. First, for given values of $\{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}\}$ and observed market quantities q_j, we back out the unique vector of non-price attributes $\boldsymbol{\xi}$ using the Berry (1994) contraction mapping. Second, given values of $\boldsymbol{\xi}$, we use minimum distance gradient-based optimization to find new values of $\{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}\}$ that match an exact-identified set of moments described below. We iterate the first and second steps until convergence. Third, we construct the demand slopes $\frac{\partial q_j}{\partial p_r}$ implied by the demand parameters from the first and second steps, and back out the marginal costs $\boldsymbol{c}$ implied by the system of first-order conditions from equation (8).

Before estimating parameters, we make the following assumptions. Our baseline scenario considers the market as of July and August 2023, with the choice set including submodels available and IRA credit eligibility as in those months. This follows our dealership survey and statistical evidence suggesting that supply chain constraints were relaxing by this period. July 2023 marked the first month that average days-to-turn for EVs exceeded 50 since before 2021, which suggests that including months prior to July would risk capturing the impact of tight supply chains. Moreover, including months after August would introduce subsequent changes to vehicle eligibility (e.g., the Tesla Model X experienced a price cut which brought it below the 30D MSRP cap) and in the set of vehicles available due to new submodel introductions.

We set market quantities q_j equal to six times their total for July plus August, representing annualized values, so we abstract from seasonality in vehicle markets. To model heterogeneous individuals by income, we define 12 representative households based on the AGI bins provided in the IRS Statistics of Income for 2023, with population weight w_h equal to that bin's share of taxpayers and income equal to the average AGI within that bin. We define the 30D tax credit income eligibility threshold at the $300,000 AGI cap for married couples.[23] We assume that each of the 131 million US households purchases a vehicle every six years as in Coşar et al. (2018), giving a potential market size of $M = 21.9$ million households per year. This is larger than the annual number of new vehicle sales to capture that some households consider a new vehicle but ultimately choose the outside option.

We find $\{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}\}$ that match eight empirical moments, summarized in Table 4. We match these moments jointly, but discuss them in order. First, we match the market share-weighted model-level own-price demand elasticity of -5.36 that Grieco, Murry, and Yurukoglu (2024) estimate for their most recent reported year. We match their elasticity instead of developing price instruments in our own data because their instruments (based on exchange rate shocks) are plausible but require many years of data. Their estimate also reflects an annual own-price demand elasticity with flexible supply, whereas the quantity variation in our complete monthly time-series data partly reflects supply constraints. Effectively, this moment targets findings from frontier research rather than reinventing the wheel for our case. Appendix Table A6 considers sensitivity to an alternative value of -4.

Second, we match the semi-elasticity of lease shares estimated in Section 5—for the Excluded August 2022 group between October–December 2022 and July–August 2023, we estimate that lease prices decreased by $5,677 relative to purchase prices, and lease shares increased by 39 percentage points (Appendix Table A2). We simulate an equivalent reduction in lease prices to match the increase in lease shares for that group of models. Intuitively, these first two moments are jointly informative about α_0 and σ^k. The own-price demand elasticity defines how many consumers substitute away from a choice while the lease share change defines how many turn to the immediate purchase or lease alternative.

[23] We take two additional steps in modeling income. First, we transform $y_{h(i)}$ into z-scores of log income, estimating the mean and standard deviation of the log-income distribution using an interval regression on the binned IRS SOI data. This means we can also interpret ξ_j as the mean vehicle preference for an average-income household (having a z-score of zero). Second, to explicitly account for the $300k threshold, we split the provided $200k-$500k bin in the IRS SOI table into a $200k-$300k bin and a $300k-$500k bin using the interval regression to impute population weights and average income under the assumption of a log-normal distribution.

Third and fourth, we match two second-choice moments from the NVES data. Among respondents who named a second choice, 53 percent of EV owners report another EV as their second choice. Additionally, 34 percent of EV owners report another EV within the same class as their second choice. These two moments are jointly informative about σ^c and σ^g, the correlation in preferences within a class and powertrain.

Finally, we match four moments from the NVES that describe heterogeneity in purchase behavior within the vehicle market. For each, we compare households with incomes above \$300,000 to households below \$300,000. In the survey, we calculate that high-income households buy cars that are on average \$12,995 more expensive (informative of α_y), are 1.99 times more likely to buy any vehicle (informative of β_0), are 12.3pp more likely to buy an EV (informative of β_{EV}), and are 0.4pp more likely to lease a vehicle (informative of β_{Lease}) than households with incomes below \$300,000. Appendix D.2 provides more information on how we calculate these statistics.

Table 5 presents the scalar parameter estimates. Since we have as many moments as parameters to estimate, we match the targeted moments exactly. We compute associated standard errors using the delta method; Appendix D.3 provides details. The standard errors are small; for example, we estimate the average price response parameter as $\alpha_0 = -0.383$ (0.023) and that low-income households are more price elastic via $\alpha_y = -0.237$ (0.004). Other parameter estimates have similar levels of precision. To explore the potential importance of modeling uncertainty, we estimate several alternative specifications—a model with no income heterogeneity, an average own-price elasticity of -4, an alternative nesting structure with domestic and foreign brands, Nocke-Schutz restrictions on supply, and a conduct assumption that firms (except Tesla) price their EVs at marginal cost—and present the results in Appendix Table A6.

Other Evidence of Model Fit

This subsection discusses eight additional types of evidence on model fit. Table 6 compares moments that the model does not formally target against reference values.[24] Along many of these dimensions, and several more that we discuss below, model fit is good though not perfect. Together, we believe this evidence suggests that the model realistically captures important aspects of the setting we study.

First, Table 5 shows that our demand system is consistent with utility maximization. in estimation, we do not impose the requirement that $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$, but our main estimates satisfy this condition with tight standard errors. This does not always occur. For example, when we estimate versions of the model that move the EV/GV nests from the top level to the second level, estimation pushes $\sigma^g < 0$, which rejects that alternative nest ordering.[25] This occurs both when the top nest is vehicle class or domestic/foreign brands. We take this as evidence that powertrain-related preferences are strong enough to support our nesting assumptions.

[24] We evaluated these other moments after fully completing model development.

[25] As these estimates are inconsistent with random utility maximization, we do not report anything further on them.

Second, Appendix Figure A16 shows that we capture heterogeneity throughout the income distribution, even though in estimation we only focus on the simple difference between aggregating households above and below the 30D income-eligibility threshold.

Third, we only target second-choice moments from the EV side of the market, but the GV second choice shares from the model and the data also align. Our estimated model implies that 95.7 percent of GV owners choose another GV as a second choice, compared to 96.8 percent in the NVES. Figure 6 shows the aggregated substitution matrix between our nine-by-nine different powertrain-segment combinations in model and the data. The correlation between the two is 0.91 when weighting cells by first-choice market share. When restricting to buyers whose first- and second-choice is an EV, the weighted correlation is 0.99. In particular, our model-implied second choices for those with an EV as their first choice (the lower portion of the left panel) match closely the patterns in the NVES data: the highest density is for substitution to within-class EVs, and the off-diagonal pattern is qualitatively quite similar.

As an example of the model's predictions, we compare second choices between the model and NVES for two prominent but different EVs. Consider the Chevrolet Bolt EV, a budget subcompact hatchback. The model predicts that the most popular second choices for the Bolt are the Tesla Model 3, the Tesla Model Y, and the Chevrolet Bolt EUV. In the NVES data, the Tesla Model 3 is also the most common second choice, with the Tesla Model Y in fifth, and the Bolt EUV in ninth. Both the model and the NVES show that sedans are a closer substitute for the Bolt than SUVs are. Second, consider the Ford Mustang Mach-E, a premium crossover SUV. The model-implied second choices for the Mustang Mach-E are the Tesla Model Y, the Tesla Model 3 and the Jeep Wrangler PHEV. Similarly, the NVES reports the Tesla Model Y as the closest second choice, with the Tesla Model 3 in fifth.[26]

Fourth, to benchmark the correlation with environmental outcomes, we calculate the average miles per gallon equivalent (MPGe) for GVs and EVs of second-choice vehicles. In the NVES, among GV buyers who consider a second choice, the second choice has an MPG of 27.6, compared to our model-estimated mean MPG of 30.0. The corresponding second choice for EV buyers in the NVES has mean MPGe of 66.6, compared to our model-estimated mean MPGe of 67.2. While these statistics suggest good fit, this moment is closely related to choice of powertrain and mean MPGe within each powertrain.

Fifth, we compare the second choices in the NVES to the model-implied second choices along US firm ownership and domestic assembly shares. In the NVES, among buyers of vehicles made by US firms, the second choice share of US firms is 62.2 percent, while the model-implied share is 38.5 percent. Domestic assembly share of second choices, conditional on the domestic assembly of the first choice, is 57.7 percent in the NVES and 39.3 percent in the model, though this is closely related to firm ownership. We acknowledge that the fit along these dimensions is imperfect, so Appendix Table A6 reports results replacing the vehicle class nest in the nested logit structure

[26]NVES respondents rarely mention the Jeep Wrangler as a second choice for the Mach-E, though the Ford Bronco, a direct competitor to the Jeep Wrangler, is in seventh as the top non-BEV vehicle.

with a US or foreign firm nest. That demand system is able to replicate these reference values. Our results are robust to this change.

Sixth, our estimates also imply an aggregate new vehicle demand elasticity of -1.1. Berry, Levinsohn, and Pakes (2004), Grieco, Murry, and Yurukoglu (2024) and the empirical evidence in Allcott et al. (2023) suggest comparable values ranging from -0.9 to -1.3. Our own-price elasticity of demand for EVs is -2.6, close to the value of -2.8 that Xing, Leard, and Li (2021) estimate.

Seventh, we estimate positive marginal costs for all submodels. We estimate that EVs have higher average marginal costs than GVs as well as greater dispersion across firms. We reiterate that our estimates reflect a combination of positive static production costs and negative dynamic benefits, and our data do not allow us to distinguish between the two. Consequently, to the extent that there is overlap in the distribution of costs between EVs and GVs, we cannot say whether this overlap reflects similar static marginal production costs with small returns to learning-by-doing, or higher EV production costs with large returns to learning-by-doing. In either case, given marginal costs, we estimate share-weighted mean markups of \$10,500 for EVs (20 percent of price) and \$8,300 for GVs (19 percent of price). This has similar magnitude to the Grieco, Murry, and Yurukoglu (2024) estimate that vehicle markups average 22 percent of price in 2018, their most recent year, though the similarity is not a high bar given that we match their mean price elasticity by design. The dispersion of implied markups across submodels ranges from \$6,700 to \$15,500, with the largest markups for Tesla; Appendix Figure A17 shows the full distribution.

Eighth, we can benchmark our estimated percentage markups to industry reports of gross profit margins, which measure a firm's accounting profit after subtracting out the cost of goods sold from sales revenue. Model-implied markups may differ from accounting profit for many reasons, including fixed costs of investment, capital depreciation, research and development activity, shadow costs of plant capacity, dynamic benefits from learning-by-doing, and tax loss harvesting. Still, we estimate that Tesla's markup as a share of revenue is 23.0 percent, which is in the range of Tesla's reported gross margin of its automotive business in 10-K filing for 2022–2023 (19.4 to 28.5 percent). Similarly, when ranking firms by their profit margin for EVs, the ordering from the model matches real-world reporting. At the extremes, the model indicates Tesla as the most profitable and Rivian the least profitable; in the middle, the model ranks GM's electric vehicle division as more proIfitable than Ford's (Boudette 2024).

6.3 Welfare and Measures of Policy Effectiveness

Social welfare has four components: consumer surplus, producer surplus, government spending, and externalities. We compute consumer surplus using the Small and Rosen (1981) log-sum formula adjusted for nested logit demand and aggregating over consumer types, denoted by $CS(\boldsymbol{p}, \boldsymbol{\tau})$. We compute producer surplus as the sum of 45W credit-inclusive markups, μ_j.[27] Subsidies provided

[27] While producer markups are endogenous to policy, we assume that the outside option (e.g., used vehicles) is competitively sold at constant markup. Since the mean indirect utility of the outside option is normalized to zero, the absolute level of utility cannot be measured. We can, however, report changes in surplus relative to a baseline scenario.

by the government have a fiscal cost that depends on the marginal cost of raising public funds (MCPF), η. Externalities arise from the production and use of choice j and consist of carbon and non-carbon components under an assumed social cost of carbon, $\phi_j = SCC \times \phi_j^{CO_2} + \phi_j^{Other}$. Appendix A.2 provides details of how we calculate these externalities.[28]

Global welfare under a given subsidy policy $(\boldsymbol{\tau}, \boldsymbol{\kappa})$ equals

$$W(\boldsymbol{\tau}, \boldsymbol{\kappa}) = \underbrace{CS(\boldsymbol{p}, \boldsymbol{\tau})}_{\text{consumer surplus}} + \underbrace{\sum_{j \in \mathcal{J}} q_j \mu_j}_{\text{producer surplus}} \underbrace{- \eta \sum_{j \in \mathcal{J}} q_j (\tau_j + \kappa_j)}_{\text{government spending}} - \underbrace{\sum_{j \in \mathcal{J}} q_j \phi_j}_{\text{negative externalities}} \tag{9}$$

Equation (9) takes the perspective of a global planner who internalizes the effects of a policy on all firms and uses a global social cost of carbon. Section 7 considers alternatives, denoted W^{US}, that describe how a domestic planner may evaluate a policy. For example, the US social planner may place no weight on foreign producer surplus, which shows up as a restricted set $\mathcal{J}_{US} \subset \mathcal{J}$ in the value of producer surplus. Or, the domestic planner may assign different values to ϕ_j, which we denote ϕ_j^{US}, such as assuming a domestic social cost of carbon or placing additional value on domestic job creation within ϕ_j^{Other}:

$$W^{US}(\boldsymbol{\tau}, \boldsymbol{\kappa}) = CS(\boldsymbol{p}, \boldsymbol{\tau}) + \underbrace{\sum_{j \in \mathcal{J}_{US}} q_j \mu_j}_{\text{domestic profits}} - \eta \sum_{j \in \mathcal{J}} q_j (\tau_j + \kappa_j) - \underbrace{\sum_{j \in \mathcal{J}} q_j \phi_j^{US}}_{\text{domestic externalities}} \tag{10}$$

We use these welfare measures to highlight the tradeoffs in green industrial policy between trade, the environment, and industrial policy goals like job creation. We separate producer surplus into components from US- versus foreign-owned firms. For calculating these statistics, we define products owned by "US firms" ($\mathcal{J}_{US}$) as Tesla, Rivian, Lucid, Ford, GM, and the former Chrysler Group brands (Chrysler, Dodge, Jeep, and Ram). We define all others as "foreign firms."[29]

In addition to welfare, our counterfactual analyses discuss two other aggregate metrics for policy evaluation: the welfare cost per ton of CO_2 abated and the marginal value of public funds (MVPF,

[28] Conceptually, for each choice, we want to compute uninternalized externalities, not directly affected by the policy changes we consider, over the life of those vehicles in the locations where they are operated. Changes in new vehicle prices induce substitution to used vehicles, taxis, ride sharing, public transportation, reduced overall mobility, and other options. We assume that the bulk of this effect involves driving used vehicles more and delaying their scrap. Since most used vehicles today are GVs, we assume that the outside option has the same externality as the average GV, except with no manufacturing CO_2 emissions.

[29] One could imagine potential modeling alternatives, such as separating producer surplus by whether vehicles are assembled in the US or abroad, or whether the supply chain primarily reflects value chain components from US allies versus other countries, or assuming a policymaker preference function which assigns positive weight to interest groups like incomes of US auto workers, analogous to Grossman and Helpman (1994). We analyze domestic versus foreign firms' producer surplus since this partition is fairly standard in the multinationals literature (Tintelnot 2017; Arkolakis et al. 2018) and is symmetric to the domestic versus foreign components of the social cost of carbon. We discuss effects on domestic employment, assembly, and batteries, which provides an alternative to distinguishing between foreign and domestic vehicles only by ownership.

see Hendren and Sprung-Keyser (2020) and Hahn et al. (2024)). We define these as

$$\begin{aligned}\frac{\text{Cost}}{\text{tonCO}_2} &= \frac{\Delta CS + \Delta PS - \Delta\text{non-CO2 negative externalities} - \Delta G}{\Delta\text{CO}_2} \\ \text{MVPF} &= \frac{\Delta CS + \Delta PS - \Delta\text{negative externalities}}{\Delta G}\end{aligned} \tag{11}$$

where CS and PS are consumer and producer surplus and G is government spending. The cost per ton abated helps to compare against alternative estimates of the social cost of carbon, though has limitations (Hahn et al. 2024). For example, it is negative for policies which reduce carbon emissions but are welfare-positive even when not considering carbon damages. To focus on the value of subsidy expenditures, our calculation of the MVPF includes only EV tax credit spending in the denominator; we interpret the gas tax as a (fiscal) externality.

For counterfactuals that decrease government spending, the MVPF may be interpreted as evaluating the higher-spending alternative. For example, when comparing the IRA to its repeal, a higher MVPF means that the additional spending on the IRA is more valuable. The MVPF can help compare against alternative estimates of the marginal cost of public funds (MCPF). The MCPF is 1 in our model with lump-sum taxes, but it exceeds 1 in a more realistic case where governments raise revenue through distortionary taxes.

6.4 Constrained Optimal Policy

This subsection discusses our methodology for estimating constrained optimal uniform and differentiated EV subsidies, subject to coverage restrictions.

Theory Our setting has two potential market failures: over-consumption due to negative externalities ϕ_j and under-consumption due to markups μ_j. We refer to the difference between price and social marginal cost, $\mu_j - \phi_j$, as the "price distortion." Below we present results when the MCPF is 1, but Appendix E shows corresponding derivations under a general MCPF, when financing subsidies generates additional distortions. We also solve for the constrained optimal consumption subsidy $\boldsymbol{\tau}$ that applies equally to purchases and leases; this counterfactual imposes no income eligibility restrictions and does not separately consider the producer subsidy $\boldsymbol{\kappa}$. In a standard model where statutory and economic incidence are independent, $\boldsymbol{\tau}$ and $\boldsymbol{\kappa}$ are perfect substitutes and infinite combinations of the two yield the same welfare (Weyl and Fabinger 2013).

Appendix E.1 derives the standard result that first-best policy for a global planner (maximizing W) implements a vector of choice-specific Pigouvian subsidies or taxes that exactly offset the price distortion: $\tau_j^{FB} = \mu_j - \phi_j$.[30] Recall that $\tau_j < 0$ represents a tax. In practice, the IRA and analogous subsidies may deviate from optimal policy for several reasons. National policymakers

[30] When the MCPF exceeds 1, the global planner equates the cost of the transfer to the government, $\eta\tau_j^{FB}$, with the combined distortions in the economy from unpriced externalities and the transfers themselves. An additional term arises from transfers to inframarginal consumers, each of whom receives a marginal unit of income at a cost of η to taxpayers.

may maximize domestic welfare, as in W^{US}. Additionally, institutions or political economy may limit policymakers to subsidizing only EVs or another subset of choices, such as vehicles meeting 30D requirements. Furthermore, policymakers may choose uniform rather than vehicle-specific subsidies.

Our expression for the uniform subsidy amount that maximizes US welfare, $\tau^{SB,U}$, requires additional notation. Let $\mathcal{S}$ denote the set of subsidized choices and let $\backslash\mathcal{S}$ denote its complement, including the outside option. Define $\mathcal{J}_{For}$ as the set of choices among foreign-owned firms, each of which receive producer surplus π_j per vehicle. Appendix E.2 derives the expression for the vector of constrained optimal differentiated subsidies that applies only to vehicles in $\mathcal{S}$ but does not restrict the subsidy to be equal across vehicles. The uniform subsidy $\tau^{SB,U}$ instead restricts the subsidy to be equal for all choices in $\mathcal{S}$. Here, demand-response weighted averages provide sufficient information to determine the subsidy level. Define $\bar{\mu}_{\mathcal{S}} \equiv (\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\mu_j)/(\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau})$ as the demand-response weighted average markup among $\mathcal{S}$ and $\bar{\phi}_{\mathcal{S}} \equiv (\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\phi_j)/(\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau})$ as the demand-response weighted average externality among $\mathcal{S}$ (correspondingly, $\bar{\mu}_{\backslash\mathcal{S}}$ and $\bar{\phi}_{\backslash\mathcal{S}}$ among unsubsidized goods).[31]

Proposition 1. *At an MCPF of one, constrained optimal uniform subsidies for a fixed subset of choices, $\mathcal{S}$, are*

$$\tau^{SB,U} = \underbrace{(\bar{\mu}_{\mathcal{S}} - \bar{\phi}_{\mathcal{S}})}_{\textit{price distortion}} - \underbrace{(\bar{\mu}_{\backslash\mathcal{S}} - \bar{\phi}_{\backslash\mathcal{S}})}_{\textit{indirect substitution}} - \underbrace{\left(\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\right)^{-1} \left(\sum_{j\in\mathcal{J}_{For}} \frac{d\pi_j}{d\tau}\right)}_{\textit{profit shifting}} \tag{12}$$

Proof. Appendix E.3. □

When only EVs receive a subsidy, the constrained optimal uniform EV subsidy equals the difference in demand response-weighted average price distortions between EVs and non-EVs, minus the marginal surplus shifted to foreign firms per marginal electric vehicle at the optimal subsidy level. Although equation (12) describes three components, when we empirically implement this formula, in some cases we aggregate the first two terms so that we report a decomposition into two components—one representing externalities and markup distortions due to encouraging sales of EVs in $\mathcal{S}$ and shifting sales away from vehicles in $\backslash\mathcal{S}$ (the first two terms in the equation); and the other representing a trade incentive to shift profits away from foreign firms (the third term).

We mention two other points. We solve for constrained optimal subsidies by treating the equation as a contraction mapping and re-computing markups, profits, and derivatives in each iteration of subsidies. Also, in the more general setting with an MCPF above one, there is an additional term in the decomposition of equation (12) corresponding to tax distortions.

Descriptive Patterns of Price Distortions The distribution of baseline (negative) price distortions across EVs and GVs (Figure 7) contributes to the constrained optimal subsidies that the

[31] Specifically, $\bar{\mu}_{\backslash\mathcal{S}} \equiv (\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau}\mu_j)/(\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau})$ and $\bar{\phi}_{\backslash\mathcal{S}} \equiv (\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau}\phi_j)/(\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau})$.

next section recovers. Figure 7 echoes the histogram of negative externalities in Figure 3, with the difference being that it includes the model-derived markup to infer social marginal cost.

Figure 7 shows several important properties about the distribution of price distortions. Panel (a) shows that at a *global SCC*, negative externalities exceed markups for almost all submodels. This implies that if policy applied to all vehicles, an EV tax rather than subsidy would be optimal. Dispersion within powertrains is driven by differences across submodels in fuel economy, weight, local pollution, and markups. This dispersion implies that vehicle-specific differentiated taxes or subsidies may outperform uniform EV subsidies. The market share-weighted average distortions are about $3,400 for EVs and $11,000 for GVs. This implies that a lower tax or higher subsidy for EVs will have indirect benefits through encouraging substitution from GVs. Furthermore, within EVs, we note that Section 30D-eligible and Section 30D-ineligible vehicles have average price distortions of $3,000 and $4,300, respectively. The strong within-EV substitution patterns our model estimates means that relaxing the 30D trade restrictions will tend to subsidize foreign EVs that have larger negative externalities.

Panel (b) of Figure 7 shows the same distributions, but valued at a *domestic SCC*. Strikingly, this change to the cost of CO_2 emissions brings the cost of externalities below markups for the majority of vehicles, implying that the majority of vehicles are priced above their domestic social marginal cost. Absent profit shifting concerns, this suggests that for a US social planner using the domestic SCC, optimal policy is a subsidy to correct for market power distortions, rather than a tax. An alternative avenue for policy, outside the scope of our analysis, would be more aggressive antitrust policy.

7 Effects of Counterfactual Policies

This section uses the equilibrium model to compare the IRA EV credits against counterfactuals.

7.1 Credit Repeal and Modified Trade and Income Restrictions

Table 7 reports results. Column 1 describes baseline outcomes under the IRA in July–August 2023.

Vehicle registrations. Panel (a) of Table 7 describes effects on total vehicle registrations. Column 2 shows effects of eliminating all EV credits. Row 4 shows that eliminating the EV credits decreases registrations of all EVs by 22 percent, or 260,000 EVs annually. Row 7 shows that eliminating the EV credits decreases the overall EV market share of new vehicle registrations by a fifth. Consistent with the IRA's "Buy American" goal, rows 5–6 show that the decrease in EV registrations is concentrated among US firms' EVs, which fall by 264,000 EVs annually, or 32 percent. Registrations of foreign firms' EVs only slightly increase. Row 8 shows that a repeal decreases leasing by a remarkable 20 percentage points, or by around two-thirds of baseline leasing rates, because this counterfactual removes the leasing loophole.

Column 3 of Table 7 shows an alternative repeal of the IRA's EV credits, reverting to pre-IRA policy as EV credits were phasing out.[32] As discussed earlier, the key difference is that pre-IRA policy in 2022 mostly subsidized foreign EVs, while the IRA's trade restrictions disproportionately subsidized US EVs. There are some similar patterns between the two repeals. Row 4 shows that reverting to pre-IRA policy decreases EV registrations, albeit by about a third as much as entirely eliminating the EV credits would. Row 8 shows that both repeals more than halve the EV leasing rate, since both effectively eliminate the leasing loophole. Row 9 shows the clearest difference between the two repeal counterfactuals—eliminating the credits decreases the US assembly share of EVs by 10 percentage points, while replacing the credits with pre-IRA policy decreases the US assembly share of EVs by 20 percentage points.

How realistic are the magnitudes of these estimated effects of the IRA EV credits on EV registrations? One benchmark comes from Germany, which in December 2023 removed a \$4,900 EV subsidy. Annualized EV sales in the first 10 months of 2024 in Germany fell by 26.6 percent (European Automobile Manufacturers' Association 2024). While the German setting and magnitude differs from the US subsidies we study, and the time series correlation may reflect other market forces, the magnitude of Germany's reduction in EV sales is in the ballpark of our projection that repealing the IRA EV credits would decrease EV registrations by 22 percent.[33]

Table 7 shows that the IRA requires substantial government spending per additional EV registered. Row 10 shows that relative to a scenario with no EV credits, the IRA spends \$26,500 of government revenue per additional EV registration. Relative to pre-IRA policy, the IRA spends \$36,500 per incremental EV registration. These statistics exceed the nominal \$7,500 in credit value because many credits go to inframarginal consumers. The model indicates that relative to the scenario with no EV credits, only 0.28 additional EVs are registered for every household that registers an EV and claims an IRA credit, i.e., an additionality rate of 28 percent. Relative to pre-IRA policy, that number falls to 16 percent.[34]

Environmental policies in other domains have broadly similar additionality rates, though some research laments these values as low. For example, Aspelund and Russo (2024) estimate that 21 to 31 percent of US Conservation Reserve Program contracts for farm conservation are additional. Chen, Ryan, and Xu (2024) finds that 28 percent of all firms are additional, though 64 percent of registrants are additional.

Auto employment, battery manufacturing and investment. Panel (b) of Table 7 shows

[32] In this scenario, \$7,500 purchase and lease credits without income eligibility restrictions were available for the first 200,000 EVs each manufacturer sold and then phased out in the year after the manufacturer reached that limit. As of July and August 2023, Tesla and GM would have received $\tau = \kappa = 0$, Toyota and Ford would have received $\tau = \kappa =$\$1,875, BMW and Stellantis would have received $\tau = \kappa =$\$3,750, and all other firms would have received $\tau = \kappa =$\$7,500. By 2024, additional manufacturers would have reached their 200,000 limit, and pre-IRA policy would have soon implied no tax credits available for any major manufacturer.

[33] An alternative US benchmark comes from the removal of EV credits under the One Big Beautiful Bill Act. EV sales in October 2025 were 30 percent lower than one year prior, though that may be especially large because dealers advertised the end date of the credits and many consumers bought EVs in the preceding months in anticipation of credit expiry (Cox Automotive 2025).

[34] This quantity-based measure of additionality mirrors the definition in Aspelund and Russo (2024) as the number of marginal households divided by the total number of households receiving credits. Since the model is discrete choice, the number of households receiving credits equals the number of credit-eligible vehicles registered.

that repealing the EV credits has important effects on two of the IRA's stated goals in domestic auto employment and domestic battery manufacturing. Row 11 shows that repealing the EV credits decreases US auto manufacturing employment by 12,000 to 15,000 jobs. Returning to pre-IRA policy decreases employment somewhat more than eliminating EV credits does because, as discussed, the pre-IRA counterfactual leads to fewer vehicles sold from US firms, and a majority of vehicles from US firms are manufactured domestically. Rows 12–13 show that about one-third of these affected workers assemble vehicles and two-thirds manufacture auto parts. Our estimates of employment changes are relative to a baseline employment of approximately 850,000 jobs across both auto parts and final assembly, so these changes represent a modest fraction of total industry employment.

Row 15 shows that relative to pre-IRA policy, the total government spending on IRA EV credits per US auto industry job created is \$169,000 per job. Relative to no credits, the spending is \$563,000 per job. As a benchmark, this is 15 to 50 times larger than the \$10,700 per job reported in Slattery (2025) for the average discretionary government subsidy awarded per promised job in their data.[35] The credits are therefore not especially cost-effective when evaluated solely as a labor market policy.

Row 14 shows that repealing the IRA also decreases the number of EV batteries assembled in the US by about a quarter million annually. The two types of repeal have fairly similar magnitudes and resemble the change in US firms' EV registrations. This is again unsurprising because many EVs from US firms are assembled domestically.

We can also use these estimates to learn about how the EV credits affect investment in EV assembly capacity. In the short- to medium-run, firms could have used excess production capacity at existing plants to meet this increased demand for EVs, but sustaining this level of production in the long-run might incur capacity investment. Appendix D.5 discusses comparisons of the increased EV registrations estimated in Table 7 to a few, large recent investments in vehicle assembly plants. This comparison reflects a small number of case studies, but it suggests that the increase in US-assembled EVs caused by the IRA is roughly on the order of \$2.4 to \$4 billion of additional investment in EV assembly. This is in the ballpark of the capacity of one or possibly two additional moderately large plants.

Social welfare. Panel (c) of Table 7 translates these market outcomes into components of social welfare. Row 16 shows that removing consumer subsidies under either type of credit repeal decreases US consumer surplus. Rows 18–19 show a pair of results that encapsulate the profit shifting aspect of industrial policy at the heart of our analysis—repealing the EV credits decreases US producer surplus but increases foreign producer surplus. Typically, repealing subsidies harms a broad set of firms in a market by lowering demand, but repealing the IRA's EV credits actually helps foreign firms operating in the US market. Rows 20–22 show that repealing the credits raises CO_2 emissions, increasing both domestic and foreign externalities. If the US planner uses the domestic

[35] Appendix A.4 explains how we calculate the number of US workers per vehicle sold. These numbers represent *job-years*, as they map the annual number of registrations to the number of workers involved. The \$10,700 figure from Slattery (2025) is per job-year.

SCC, then a repeal increases foreign externalities three to five times more than it increases domestic externalities. These patterns are also at the heart of our finding that the IRA in environmental terms benefits foreign countries more than it benefits the US because it contributes to the global public good of greenhouse gas mitigation. Carbon mitigation cooperatively addresses global negative externalities while profit shifting non-cooperatively decreases foreign welfare. Rows 25–28 sum this all up. Repealing the EV credits decreases global surplus because the resulting decline in market surplus exceeds the resulting increase in negative externalities.

Panel (d) of Table 7 reports the welfare cost per ton of CO_2 abated. Since the IRA's EV credits raise domestic welfare while reducing CO_2 emissions, row 30 shows that the cost per ton from the domestic planner's perspective is negative. This can be be interpreted as justifying policy under any level of CO_2 damages. From the global planner's perspective, the marginal abatement cost is positive at $60 per ton relative to no EV credits, and $14 per ton relative to pre-IRA policy.

Panel (e) of Table 7 shows the MVPFs of these policies. These vary from modest to moderate. From the global planner's perspective, the IRA credits generate $1.15 to $1.28 in benefits per dollar of government spending. This is not a large MVPF, either relative to other policies (Hahn et al. 2024) or to common estimates of the marginal cost of public funds (Finkelstein and Hendren 2020). Rows 32–33 show that, relative to pre-IRA policy, the US planner has a higher MVPF for the IRA EV credits than the global planner does. This is surprising because in typical climate change settings, the global planner values the global public good of greenhouse gas mitigation more than the national planner does. Profit shifting in the IRA EV credits relative to pre-IRA policy explains why this setting has the opposite pattern than a typical climate policy does. This asymmetry between the IRA's domestic and foreign impacts also reflects domestic political economy: passing the IRA involved support from domestic manufacturing and labor interest groups, who valued the IRA's trade restrictions, and from environmental interest groups, who valued its climate change mitigation.

Appendix Table A4 reports bootstrapped 95 percent confidence intervals; Appendix D.3 describes how we compute these. The tight confidence intervals reflect our precise parameter estimates. For example, our confidence interval for the impact of eliminating the EV credits on EV registrations ranges from 247,000 to 272,000. Similarly, our estimate of the confidence interval for the change in auto manufacturing jobs is 11,700 to 12,900.

Appendix Table A5 considers settings with a marginal cost of public funds equal to 1.4, which Finkelstein and Hendren (2020) consider as a benchmark, and alternative SCC values of $100 or $200; Appendix D.4 discusses these sensitivity analyses. With a marginal cost of public funds equal to 1.4, compared to no EV credits, the IRA EV credits decrease US and global welfare. In most scenarios, the change in US surplus exceeds the change in global surplus, due to profit shifting.

Appendix Table A6 considers alternative specifications of demand and supply, which generally support our headline results. Broadly, model uncertainty has somewhat similar magnitude importance as statistical uncertainty—across these different model assumptions, the variation in key magnitudes like lease and US assembly shares, CO_2 emissions, MVPF, and cost per additional EV have a somewhat similar range as the confidence intervals reported in Appendix Table A4.

The final column of Appendix Table A6 considers a scenario that restricts the scope of profit shifting by assuming non-Tesla EVs charge zero markup, effectively lowering prices to expand dynamic benefits from learning-by-doing. We interpret this as extreme since near-term profits and market power are potentially meaningful in this setting. In this scenario, the EV credits reduce US surplus, and, from the US planner's perspective, the IRA EV credits have an MVPF below one compared to the counterfactual of no credits. This echoes our broader narrative that profit shifting plays a central role in evaluation of these policies; assuming away profits decreases the resulting domestic benefits.

Modifying trade restrictions. Columns 4–5 of Table 7 add trade restrictions for leases or remove trade restrictions for purchases. These counterfactuals mostly close the incentive to lease foreign vehicles, though not entirely as they preserve the income and MSRP eligibility restrictions on purchases.

Panel (a) of Table 7 shows that trade restriction and trade relaxation generally produce opposite-signed effects on market outcomes. Relative to the IRA baseline, row 4 shows that adding trade restrictions to leases slightly decreases EV registrations, while removing trade restrictions moderately increases EV registrations. Row 9 shows that adding trade restrictions to leases increases the share of EVs assembled in the US, while removing trade restrictions for purchases decreases this share by 9 percentage points. Row 8 shows that both counterfactuals decrease the lease share by around half relative to the baseline leasing rate, since both counterfactuals treat purchases and leases nearly symmetrically. The lease rate in these trade counterfactuals remains slightly above the lease rate in the counterfactuals that repeal the IRA because these trade counterfactuals leave the IRA's income eligibility restrictions unchanged.

Panel (b) of Table 7 shows that the credits' trade restrictions increase US auto employment and battery assembly, although the magnitudes are small. Column 4 shows that closing the leasing loophole by adding trade restrictions on leasing adds 750 jobs to the US auto sector, which is positive in sign but minuscule in magnitude. Column 5 shows that allowing buyers to receive the credits when purchasing a vehicle decreases US auto manufacturing employment by about 3,500 jobs. Row 14 shows that these trade counterfactuals also change the number of EV batteries assembled in the US by 10,000 to 30,000 per year. These magnitudes of mostly closing the leasing loophole are less than a tenth of the magnitude of the effects of the EV credits overall compared to repeal.

Panel (c) of Table 7 shows that the leasing loophole has poor welfare properties. Row 23 shows that closing the loophole, either by adding trade restrictions on leases or removing them for purchases, increases global welfare. Row 24 shows the same conclusion from the US planner's perspective using the global SCC. Row 25 shows that under the domestic SCC, adding trade restrictions to leases would also increase US welfare, although removing trade restrictions for purchases slightly decreases US welfare. Panel (e) shows that the MVPF looks even worse. From the US planner's perspective, the MVPF of the leasing loophole ranges between 0.45 and 1.11, depending which social cost of carbon is used and whether the loophole is closed by changing policy for leases or purchases. None of these MVPF values are particularly high.[36]

A few reasons explain why the leasing loophole performs poorly. Row 20 of Table 7 shows that the credits' "Buy American" provisions harm the environment since these trade restrictions increase CO_2, and since trade liberalization decreases CO_2. The large leasing changes shown in row 8 demonstrate that more consumers will lease with sufficient incentives, but the large magnitude of the required subsidies makes these subsidies relatively inefficient.

Overall, the trade restrictions reveals tradeoffs between trade and the environment, and between foreign and domestic firms. Liberalizing trade benefits US consumers, by increasing the choice set of subsidized vehicles, and increases EV registrations, thereby reducing global negative externalities, but harms domestic producers. The greater weight and electricity consumption of "foreign" (30D-ineligible) models moderates this tradeoff.

Removing income restrictions. The IRA incorporated income restrictions on credits, partly to address the credits' regressivity and limit its fiscal impact. In the years 2006–2021, households with annual incomes above \$200,000 received a majority of EV credits (Borenstein and Davis 2025). Appendix Figure A6 shows similar patterns in our data. Of course, the leasing loophole relaxes the credits' income restrictions, since high income buyers who leased could still qualify for credits. Column 6 of Table 7 removes the income eligibility restrictions in the 30D tax credits. This preserves the trade aspect of the leasing loophole, but eliminates the incentive for households with high incomes to lease.

Column 6 of Table 7 shows that removing the income restrictions slightly increases EV registrations, substantially increases the EV market share of US firms, and decreases CO_2 emissions. Row 31 shows that removing income restrictions has an MVPF of 1.46 from the global planner's perspective, because it decreases CO_2 and so addresses global externalities. The MVPF is higher from the US planner's perspective because the US planner benefits from profit shifting in addition to lower CO_2.

Overall, we calculate that the trade restrictions explain most of the total observed increase in leasing, and the income restrictions explain little. This counterfactual change in the EV credits' income restrictions lets us assess how much of the observed increase in leasing reflected the leasing loophole for income versus trade restrictions. As discussed previously, imposing trade restrictions on leases while maintaining the income restrictions lowers the EV lease share by 16.4 percentage points. Conversely, removing the income restrictions while maintaining the trade limits only lowers the EV lease share by 2.8 percentage points. Since eliminating EV credits entirely lowers the lease share by 19.5 percentage points, almost the same amount as the combined effect of the two changes, we conclude that the trade restrictions account for about 85 percent (=16.4/19.5) of the observed total change in leasing, and the income restrictions account for the rest.

[36] Because column 4 of Table 7 decreases government spending, the MVPF describes the higher-spending alternative, i.e., it describes the MVPF of adding the leasing loophole in the IRA. Since this value is below one, the leasing loophole is not an effective use of government spending and removing the loophole would be welfare improving.

Removing the income restrictions, however, does increase the credits' regressivity. Row 35 shows that under the IRA, 44 percent of households earning above the threshold who purchased an EV obtained the credits. Among high income households choosing EVs, the income restrictions decreased the share receiving credits by about 33 percentage points. Clearly, the income restrictions trade off climate benefits against redistribution. The income restrictions decreased the credits' regressivity and saved the government money, but the leasing loophole shifted EV registrations to foreign firms and to modestly less environmentally friendly vehicles.

7.2 Constrained Optimal Policies

This subsection analyzes the magnitude of constrained optimal subsidies, following the theoretical discussion in Section 6.4. Column 1 of Table 8 shows observed values under the IRA. The counterfactual in column 2 preserves the IRA's 30D restrictions on which submodels qualify for credits, but replaces the $7,500 IRA credit with the value of the single, uniform subsidy across submodels that maximizes US total surplus using the domestic SCC.[37] Column 3 allows the US planner to value domestic auto manufacturing jobs (including for EVs and GVs) at $10,700 per job, as in Slattery (2025). Column 4 lets the planner assign different subsidy amounts to each eligible submodel. We calculate uniform subsidies in columns 2–3 using equation (12); we calculate the differentiated subsidies in column 4 using equation (31) in Appendix E.2. Panel (a) shows market aggregates; panels (b)–(d) show differences relative to a no EV subsidy baseline.

We do not believe that policymakers in 2022 purposefully chose the $7,500 actual credit value; since they merely left it unchanged in nominal terms from earlier legislation. We study these specific counterfactuals to gain insight on the optimality of IRA subsidies within the framework of our model. Comparing uniform with differentiated subsidies measures the gains from differentiation. Comparing policy with and without value for domestic manufacturing jobs quantifies the importance of labor-related political economy considerations. In a neoclassical model of an economy at full employment, creating jobs in a sector does not affect aggregate welfare, since it merely reallocates employment between sectors. Under other assumptions, however, labor market frictions or changes in local economic activity may generate welfare consequences to labor in particular regions or sectors (Bartik 2015).

Row 1 of Table 8 shows that a uniform subsidy of $9,606 for 30D-eligible submodels maximizes US welfare. This is about thirty percent above the actual IRA mean credit amount shown in column 1.[38] Appendix Table A7 reports the decomposition of the subsidy following equation (12) and shows

[37] We apply these restrictions to the submodel as a whole and allow both purchases and leases to claim the subsidy if a submodel is eligible, regardless of household income.

[38] The actual mean IRA credit amount, shown in column 1, is slightly below $7,500 because some vehicles only qualify for $3,750 in credits due to battery or critical mineral supply chains only satisfying one of the two requirements imposed in April 2023. We compute the mean credit amount conditional on 30D or 45W credit receipt, assuming the full credit amount is claimed by taxpayers. In reality, households with lower tax liability may claim less than the full amount of the credits due to their non-refundability (Borenstein and Davis 2025). We account for income eligibility by omitting high-income households purchasing 30D-eligible vehicles from the average, though high-income households who lease EVs are included.

that profit shifting incentives account for 40 percent of the uniform subsidy value. Relative to the IRA baseline in column 1, this higher subsidy in column 2 increases annual EV registrations by 101,000. Since the uniform subsidy treats purchases and leases symetrically, EV leasing rates fall by over one-half. Rows 19–20 show that the combination of increasing the uniform subsidy level and closing the leasing loophole increases US welfare from the IRA baseline by $1.2 to $1.7 billion annually, depending on the social cost of carbon. Differentiating credits among vehicles as in column 4 increases US welfare by $2.1 to $3.3 billion annually. Uniform subsidies therefore achieve between one-half and two-thirds of the welfare gains from differentiation.

Although domestic manufacturing employment was one leading rationale for the credits, we find that the constrained optimal subsidy when numerically accounting for policymaker preference for employment as in Slattery (2025) changes little. Under the domestic SCC and assuming an MCPF of 1, accounting for the potential policymaker value for auto manufacturing employment raises the constrained optimal EV subsidy by about 5 percent. Compared to that baseline uniform subsidy in column 2 of Table 8, this higher subsidy increases government spending by $1 billion annually and increases domestic auto manufacturing jobs by only 1,500. The fiscal cost per additional job is an order of magnitude greater than the $10,700 job value used in the planner's objective. This echoes the finding in Slattery (2025), albeit from a completely different setting, that "the number of new jobs the firm promises only explains about 10% of observed subsidies."

Appendix D.4 discusses subsidy calculations under several alternative parameter assumptions, presented in Appendix Tables A5 and A7. We consider other SCC values and values of the marginal cost of public funds. We also report the constrained optimal uniform subsidy across alternative model assumptions as a row in Appendix Table A6. The primary qualitative conclusions persist, though some magnitudes vary.

8 Conclusion

The IRA was forecast to cost up to a trillion dollars (Bistline, Mehrotra, and Wolfram 2023), making it among the most costly potential climate change investments in human history. It proved short-lived, however, as just three years in, the One Big Beautiful Bill Act reversed most of its provisions. We provide the first ex post microeconomic welfare analysis of a central component of the IRA—tax credits to subsidize the purchase of new EVs, partly conditional on requirements that supply chains locate in the US or allied countries. We assemble detailed data from numerous sources on vehicle prices, quantities, leasing, subsidies, and environmental impacts. We present descriptive facts on the market, event studies around the implementation of the tax credits, and an equilibrium model of supply and demand to assess welfare impacts. In doing so, we also use this setting to illustrate more general lessons on tradeoffs between foreign and domestic interests and between trade and the environment.

Our event studies show that in the IRA's inaugural year, the credits substantially increased leasing, in line with trade, income, and price restrictions on eligibility. Our short-run event study analysis also finds suggestive evidence that consumers received most of the credits' price impact, though we interpret this evidence cautiously given evolving supply conditions at this time.

Our equilibrium model implies that the IRA's EV credits have an MVPF of 1.1 to 2, through shifting profits from foreign to domestic firms and decreasing negative externalities, though several scenarios have substantially different consequences from the global versus US planner's perspective.

Our analysis of the IRA's EV credits highlights the important role of heterogeneity in externalities among EVs more broadly. Countries are implementing a wide range of policies to encourage vehicle electrification, many without a focus on which EVs consumers adopt. For example, subsidies to charging infrastructure are hard to target among different EVs. We find that the variation in externalities within EVs versus GVs have similar magnitudes and considerable overlap, such that that failing to subsidize (or tax) EVs proportionally to their heterogeneous externalities misses substantial opportunities for policy to increase welfare. Of course, our results reflect our externality assumptions, which we have developed carefully but still reflect the state of the literature.

More broadly, our analysis highlights tradeoffs in green industrial policy between foreign and domestic interests, and between trade and the environment. Traditionally, trade policy either represents a cooperative instrument (e.g., Most Favored Nation tariffs) or a non-cooperative instrument (e.g., "Schedule 2" tariffs that apply to US imports from North Korea). Green industrial policy, unusually, has both cooperative and non-cooperative elements within a single policy. The industrial policy component is non-cooperative, as it seeks to exploit profit shifting to relocate growing clean energy production domestically. The green component invests in the global public good of CO_2 mitigation that partly benefits foreign countries, and may even use a cooperative perspective on the environmental externality (e.g., the global SCC) to design and evaluate regulation.

While economists lament that countries are increasingly using trade restrictions to advance climate change policy, partly led by the IRA, some policymakers celebrate this combination. The global public goods nature of climate change mitigation can make voters and policymakers reluctant to implement unilaterally stringent climate mitigation. Pairing climate change policy with trade restrictions has provided political support for a growing set of green policies. Our analyses help illustrate why—incorporating profit shifting into the domestic assessment of green policy increases its domestic welfare gains, though generally at the expense of foreign surplus. Of course, as more countries pair trade restrictions with climate change policy, global costs of trade restrictions grow.

We leave several unanswered questions. Focusing specifically on EV credits, an important line of inquiry can study longer-run impacts of even temporary subsidies, as resulting relocation of supply chains, learning-by-doing, and interactions with EV charging infrastructure could generate important welfare and distributional effects. International reallocation of production due to the IRA may require substantial movement of capital and other assets, and possibly distortions to production scale (e.g., firms may duplicate production of a submodel across plants in different countries). This could make dynamic estimates of costs exceed the static estimates that we provide.

Despite elimination of most IRA components under the One Big Beautiful Bill Act in 2025, broader analysis of the IRA may also provide insight for ongoing and future research. Many of the IRA's over 80 separate components have some attributes in common with the EV credits we study—domestic content requirements, tax credits for green technologies, and extensions of prior and smaller tax credits. Understanding what conclusions generalize across provisions of the IRA would be valuable. Additionally, in response to the IRA, some US trading partners are considering or implementing their own green industrial policies. Just as research has studied Nash tariffs by nesting quantitative trade models within a game between countries (Ossa 2014), so too it might be informative to study how the incentives for green industrial policy change when analyzing it as strategic environmental policy choice among countries.

Why do countries design climate policy that benefits foreign countries, but via industrial policy, which non-cooperatively shifts profits? International competition in industrial policy for a given industry to some extent reflects a zero-sum game, while the climate is a global public good. In evaluating their priorities, what weight do policymakers in one country effectively put on environmental benefits abroad? Regular international negotiations encourage weights above non-cooperative zero on foreign climate benefits, but perhaps not equal to one. Domestic political economy likely contributes to these decisions, though its exact mechanisms are unclear. Interest groups also play a role—organized lobbies like auto firms benefit from industrial policy and create domestic political pressure for non-cooperative policy. Our analysis studies this leading example of green industrial policy, but it cannot explain all of the tensions that we have highlighted.

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Table 1: **Summary Statistics**

	Mean	Std. dev.	Min.	Max.	Obs.
Registrations	1,079	1,887	26	38,781	19,019
Purchase price ($000s)	51.3	19.3	12.7	96.7	17,691
Lease price ($000s)	48.1	20.9	16.3	372.3	15,746
Percent leased	25.1	17.8	0	100	19,019

Notes: This table presents summary statistics for our submodel-by-month panel of new vehicle sales and prices for 2022 and 2023. Registration counts are from Experian. Purchase prices are from the California DMV; lease prices are computed from combining lease term data from Cox Automotive with purchase prices from the California DMV.

Table 2: **Share-Weighted Average Externalities by Vehicle Powertrain**

	(1)	(2)	(3)	(4)	(5)
	Electric Vehicles				
	All EVs	Battery electric vehicles	Plug-in hybrids	Gasoline vehicles	Structural model outside option (used GVs)
Manufacturing + scrap CO_2 (global SCC)	2,974	3,142	2,156	1,815	–
Driving CO_2 (global SCC)	6,958	6,042	11,389	13,597	13,597
Driving local pollutants	559	558	561	377	377
Excess weight in accidents	9,277	9,114	10,069	7,058	7,058
Positive fiscal externality	(5,764)	(5,807)	(5,558)	(3,520)	(3,520)
Total negative externality					
Global SCC	14,003	13,050	18,617	19,327	17,513
Domestic SCC	5,215	4,923	6,631	5,689	5,480

Notes: This table presents market share-weighted average lifetime externalities across submodels within a powertrain, weighting submodels by average monthly sales in months when the submodel was available. Units are $/vehicle. Positive fiscal externalities are shown in parentheses to emphasize they are opposite-signed to damages.

Table 3: **Variation in Externalities by Powertrain**

	Coefficient of variation				Interdecile ratio			
	EVs			GVs	EVs			GVs
	BEVs	PHEVs	all		BEVs	PHEVs	all	
Panel (a): Global SCC								
Total negative externalities	0.24	0.23	0.25	0.25	1.06	1.05	1.08	1.07
			[0.946]				[−0.01, 0.01]	
Carbon damages	0.11	0.22	0.20	0.19	1.03	1.08	1.05	1.05
			[0.600]				[−0.01, 0.01]	
SMC minus price	0.54	0.42	0.52	0.38	1.13	1.11	1.19	1.12
			[0.000]				[0.02, 0.14]	
Panel (b): Domestic SCC								
Total negative externalities	0.44	0.28	0.39	0.50	1.12	1.08	1.11	1.17
			[0.014]				[−0.09, −0.03]	
Carbon damages	0.11	0.22	0.20	0.19	1.04	1.10	1.07	1.06
			[0.600]				[−0.01, 0.02]	
SMC minus price	-1.18	-1.03	-1.17	-1.00	-	-	-	-
			[0.212]				-	

Notes: All quantities are computed at the submodel level, unweighted. Interdecile ratio is the 90th sample percentile divided by the 10th sample percentile of log externalities. BEVs are battery electric vehicles, PHEVs are plug-in hybrid electric vehicles. SMC is social marginal cost, computed as the sum of each submodel's marginal cost of production with its negative externalities. As the 10th percentile of this measure is negative, we cannot report the interdecile ratio in Panel (b). Bracketed values in the Coefficient of variation column are p-values for the difference in coefficients of variation between GVs and all EVs, computed following Feltz and Miller (1996); bracketed values in the Interdecile ratio column are bootstrapped 95 percent confidence intervals for the difference in interdecile ratio between GVs and all EVs.

Table 4: **Parameter Assumptions and Empirical Moments**

Description	Source	Target Value	Model Value
Market size (million/year)	Federal Reserve Bank of St. Louis (2024c)	21.9	–
Population shares and average income	Internal Revenue Service (2023), Table 2	–	–
Model-level demand elasticity	Grieco, Murry, and Yurukoglu (2024)	-5.36	-5.36
Share of EV buyers whose 2nd choice is EV	NVES	53.1%	53.1%
Share of EV buyers whose 2nd choice is an EV in the same vehicle class	NVES	34.2%	34.2%
Difference in average transaction prices, high- vs. low-income households	NVES	\$13,647	\$13,647
Ratio of inside good choice probability, high- vs. low-income households	NVES, Internal Revenue Service (2023)	1.99	1.99
Difference in EV choice propensity, high- vs. low-income households	NVES	13.6pp	13.6pp
Difference in lease choice propensity, high- vs. low-income households	NVES	0.5pp	0.5pp
Excluded Aug 2022 group lease price change	Appendix Table A2	-\$5,677	–
Excluded Aug 2022 group lease share effect	Appendix Table A2	39%	39%

Notes: This table presents empirical moments we match and other parameter assumptions used in the demand estimation in Section 6. High-income households are those that report income above $300,000 in the survey; low-income households are those that report income below $300,000 in the survey. Refer to Appendix D.1 for additional details on computing the moments.

Table 5: **Parameter Estimates**

Parameter	Description	Value	Standard error
α_0	Price response parameter	-0.383	0.023
α_y	Price response × income interaction	-0.237	0.004
β_0	Inside good × income interaction	0.478	0.067
β_{EV}	EV × income interaction	0.530	0.008
β_{Lease}	Lease × income interaction	0.031	0.002
σ^g	EV-GV nest parameter	0.388	0.009
σ^c	Class nest parameter	0.530	0.007
σ^k	Submodel nest parameter	0.880	0.019

Notes: This table presents parameter estimates from the demand estimation in Section 6.

Table 6: **Moments Not Formally Targeted: Measures of Model Fit**

Statistic	Model Value	Reference Value
Panel (a) Second Choice Measures		
Share of GV buyers with GV second choice	95.7%	96.8% (NVES)
Average MPG(e) of second choice, EV buyers	67.2	66.6 (NVES)
Average MPG(e) of second choice, GV buyers	30.0	27.6 (NVES)
US firm share of second choices, US firm first choice	38.5%	62.2% (NVES)
Domestic assembled share of second choices, domestic assembled first choice	39.3%	57.7% (NVES)
Correlation (share-weighted), class-powertrain aggregate second choices	0.91	(Figure 6)
Correlation (share-weighted), class-powertrain aggregate second choices, EV first and second choice	0.99	(Figure 6)
Panel (b): Price Measures		
Aggregate new vehicle market demand elasticity	-1.1	-1 (Berry, Levinsohn, and Pakes 2004) -1.29 (Grieco, Murry, and Yurukoglu 2024)
Aggregate EV demand elasticity	-2.6	-0.92 (Allcott et al. 2023) -2.8 (Xing, Leard, and Li 2021)
Pass-through of lease credits to lease prices relative to buy prices	$8,022	$4,055 to $7,299 (Appendix Table A2)
Pass-through of IRA credits to purchase prices	$7,024	$6,879 to $8,865 (Section 5.2)
Share-weighted average markup	20% (EV) 19% (GV)	22% (Grieco, Murry, and Yurukoglu 2024)

Notes: This table presents statistics on data moments that we do not formally target, as discussed near the end of Section 6.2. All second choice statistics are weighted by the market share (or survey share) of the first choice unless otherwise specified. The range of reference values for pass-through are the 95 percent confidence intervals of our regression estimates.

Table 7: **Effects of Counterfactual Policies on Market and Welfare Outcomes**

		(1)	(2)	(3)	(4)	(5)	(6)
			Repeal IRA		Modify Trade Limits		
		IRA (baseline)	Eliminate EV Credits	Return to Pre-IRA 30D with phaseout	IRA, add trade restrictions on leases	IRA, remove trade restrictions	IRA, remove income threshold
	Panel (a): Market Aggregates under Counterfactual Scenario						
1.	Vehicle registrations (000s/year)	10,633	10,519	10,596	10,613	10,688	10,634
2.	US firms (000s/year)	4,017	3,804	3,738	4,027	3,970	4,032
3.	Foreign firms (000s/year)	6,616	6,714	6,858	6,586	6,718	6,602
4.	EV registrations (000s/year)	1,184	924	1,117	1,134	1,313	1,199
5.	US firms (000s/year)	835	571	543	834	812	856
6.	Foreign firms (000s/year)	349	353	574	300	501	343
7.	EV market share (%)	11.1	8.8	10.5	10.7	12.3	11.3
8.	Lease share, within EVs (%)	29.3	9.8	10.8	12.9	15.4	26.5
9.	US assembly share, within EVs (%)	70.5	61.0	50.6	73.8	61.3	71.3
10.	Cost per additional EV ($000s/EV)	-	26.5	36.5	31.9	13.5	40.3
	Panel (b): Employment and Battery Production Effects Relative to IRA Baseline (000s/year)						
11.	ΔUS auto manufacturing jobs	-	-12.3	-14.5	0.7	-3.5	0.7
12.	ΔUS auto parts jobs	-	-7.8	-9.3	0.5	-2.3	0.5
13.	ΔUS auto assembly jobs	-	-4.5	-5.2	0.2	-1.2	0.2
14.	ΔUS-assembled EV batteries	-	-258	-289	11	-34	19
15.	Cost per additional US job ($000s/job)	-	563	169	-2,160	-499	877
	Panel (c): Surplus Effects Relative to IRA Baseline ($billion/year)						
16.	ΔUS consumer surplus	-	-4.84	-0.88	-1.08	2.33	0.67
17.	ΔGlobal producer surplus	-	-1.63	-1.37	0.10	-0.05	0.08
18.	ΔUS producer surplus	-	-2.56	-3.67	0.35	-0.95	0.28
19.	ΔForeign producer surplus	-	0.93	2.30	-0.25	0.90	-0.20
20.	ΔCO_2 emissions (million tons/year)	-	5.74	3.03	0.51	-2.14	-0.50
21.	ΔGlobal neg. exter. (global SCC)	-	1.47	0.89	0.11	-0.55	-0.13
22.	ΔUS neg. exter. (domestic SCC)	-	0.25	0.24	0.00	-0.10	-0.02
23.	ΔForeign neg. exter. (foreign SCC)	-	1.22	0.65	0.11	-0.46	-0.11
24.	ΔUS government spending	-	-6.90	-2.45	-1.61	1.74	0.60
25.	ΔGlobal surplus	-	-1.04	-0.69	0.52	1.09	0.28
26.	ΔUS total surplus (global SCC)	-	-1.97	-2.99	0.77	0.19	0.48
27.	ΔUS total surplus (domestic SCC)	-	-0.74	-2.35	0.88	-0.27	0.37
28.	ΔForeign total surplus (foreign SCC)	-	-0.30	1.66	-0.36	1.36	-0.09
	Panel (d): Welfare Cost per Ton of CO_2 Abated						
29.	US cost/ton CO_2 abated ($/ton)	-	-101	-747	1,759	152	-719
30.	Global cost/ton CO_2 abated ($/ton)	-	59.8	13.8	1,269	-268	-318

Continued on next page

Table 7 (continued from previous page)		(1)	(2)	(3)	(4)	(5)	(6)
			Repeal IRA		Modify Trade Limits		
		IRA (baseline)	Eliminate EV Credits	Return to Pre-IRA 30D with phaseout	IRA, add trade restrictions on leases	IRA, remove trade restrictions	IRA, remove income threshold
	Panel (e): MVPF of Higher-Spending versus Lower-Spending Scenario						
31.	Global MVPF	-	1.15	1.28	0.68	1.63	1.46
32.	US MVPF (global SCC)	-	1.28	2.22	0.52	1.11	1.79
33.	US MVPF (domestic SCC)	-	1.11	1.96	0.45	0.85	1.61
	Panel (f): Allocation of EV Credits						
34.	Share of EVs with credits (%)	79.7	0.00	65.9	66.8	87.8	86.8
35.	Among HHs >$300k (%)	44.0	0.00	64.8	23.0	41.5	78.7

Notes: This table presents counterfactual simulation results for the IRA and alternative policies. In column 2, all 30D and 45W credits are set to zero. In column 3, we simulate EV credits as they would have been in July-August 2023 had the IRA not passed. Under the pre-IRA Section 30D, all EVs (purchased or leased) are eligible for credits until the 200,000-vehicle cap. Given cumulative sales volumes through mid-2023, we assume no credit for Chevrolet and Tesla, 1/4 credit for Toyota and Ford, 1/2 credit for BMW and Stellantis. In column 4, we apply the Section 30D trade restrictions to all leases, although the buyer income restrictions still do not apply to leases. In column 5, all vehicles are eligible under Section 30D regardless of assembly location or battery sourcing, although buyer income restrictions and MSRP caps still apply. In column 6, we remove the $300,000 income restriction on purchases. New vehicle registrations include only leases and purchases by individuals, not vehicles sold to organizations. "US firms" denotes vehicles produced by US-owned firms, including the traditional US brands in Stellantis. "US assembly" denotes vehicles assembled in the US, regardless of firm ownership. Rows with Δ refer to changes relative to the IRA baseline. "Global surplus" equals the sum of consumer surplus, US producer surplus and foreign producer surplus less government spending and negative externalities. "US total surplus" equals global surplus minus foreign automakers' producer surplus. "Foreign SCC" is global SCC minus domestic SCC. Costs of abatement are in terms of social welfare; they are negative when a policy change results in lower carbon emissions and increased social welfare disregarding the direct effect of carbon damages. Cost per additional EV is the ratio of Δ government spending to Δ new EVs registered relative to the IRA. Cost per additional US job is the ratio of Δ government spending to Δ US manufacturing job relative to the IRA. The marginal value of public funds (MVPF) equals (Δ consumer surplus + Δ producer surplus - Δ negative externalities)/(Δ government spending). The "US MVPF" values are computed with Δ US producer surplus in the numerator, while the "Global MVPF" uses Δ global producer surplus in the numerator.

Table 8: **Counterfactual Simulation Results: Optimal Subsidies**

		(1)	(2)	(3)	(4)
		IRA	US-optimal uniform EV subsidy, 30D restrictions	US-optimal uniform EV subsidy, 30D restrictions, valuing jobs	US-optimal differentiated EV subsidy. 30D restrictions
	Panel (a): Market Aggregates under Counterfactual Scenario				
1.	Mean EV subsidy in this counterfactual	\$7,314	\$9,606	\$10,111	\$11,928
2.	(Standard deviation)	(815)	(0)	(0)	(3,279)
3.	Vehicle registrations (000s/year)	10,633	10,672	10,684	10,702
4.	EV registrations (000s/year)	1,184	1,291	1,317	1,347
5.	US firms	835	1,028	1,058	1,127
6.	Foreign firms	349	263	259	220
7.	EV market share (%)	11.1	12.1	12.3	12.6
8.	Lease share, within EVs (%)	29.3	11.1	11.2	8.9
9.	US assembly share, within EVs (%)	70.5	77.8	78.5	79.7
	Panel (b): Surplus Effects Relative to No EV Subsidy Baseline (\$billion/year)				
10.	ΔUS consumer surplus	4.84	7.36	7.89	8.23
11.	ΔGlobal producer surplus	1.63	2.43	2.61	4.30
12.	ΔUS producer surplus	2.56	4.61	4.91	6.97
13.	ΔForeign producer surplus	-0.93	-2.17	-2.30	-2.66
14.	ΔGlobal neg. externalities (global SCC)	-1.47	-1.79	-1.92	-3.32
15.	ΔUS neg. externalities (domestic SCC)	-0.25	-0.20	-0.21	-0.93
16.	ΔForeign neg. externalities (foreign SCC)	-1.22	-1.59	-1.71	-2.39
17.	ΔUS government spending	6.90	10.0	10.9	13.3
18.	ΔGlobal surplus	1.04	1.54	1.52	2.55
19.	ΔUS total surplus (global SCC)	1.97	3.71	3.82	5.22
20.	ΔUS total surplus (domestic SCC)	0.74	2.12	2.11	2.83
21.	ΔForeign total surplus (foreign SCC)	0.30	-0.58	-0.59	-0.27
	Panel (c): Impacts on CO_2				
22.	ΔCO_2 emissions (million tons/year)	-5.74	-7.47	-8.01	-11.2
23.	Global cost/ton CO_2 abated (\$/ton)	59.8	35.2	51.9	13.2
24.	US cost/ton CO_2 abated (\$/ton)	-101	-255	-235	-225
	Panel (d): MVPF versus No EV Subsidy				
25.	Global MVPF	1.15	1.15	1.14	1.19
26.	US MVPF (global SCC)	1.28	1.37	1.35	1.39
27.	US MVPF (domestic SCC)	1.11	1.21	1.19	1.21
28.	Cost per additional EV (\$000s/EV)	26.5	27.4	27.7	31.4
29	ΔUS auto manufacturing jobs (000s)	12.3	22.4	23.9	21.2
30.	Cost per additional US job (\$000s/job)	563	449	457	628

Notes: This table presents counterfactual simulation results for the IRA and alternative policies, relative to a common baseline of no EV subsidies (column 2 in Table 7). In column 2, we simulate the uniform EV subsidy, subject to Section 30D trade restrictions, that maximizes US total surplus with the domestic SCC. In column 3, we assume the planner values annual US jobs as \$10,700 per job. In column 4, we simulate the choice-specific differentiated EV subsidy that maxiumizes US total surplus with the domestic SCC. New vehicle registrations include only leases and purchases by individuals, not vehicles sold to organizations. Mean and standard deviation of subsidies are sales-weighted across EV models conditional on positive 30D or 45W credit amount, accounting in column 1 for income-eligibility using the model-implied income distribution. The marginal value of public funds (MVPF) equals (Δconsumer surplus + Δproducer surplus - Δnegative externalities)/(Δ government spending). The "US MVPF" values are computed with ΔUS producer surplus in the numerator, while the "Global MVPF" uses Δglobal producer surplus in the numerator. "US total surplus" equals "[global] total surplus" minus foreign automakers' producer surplus. Costs of abatement are negative when a policy change results in lower carbon emissions but is welfare-positive even when disregarding carbon damages. Cost per additional EV is the ratio of Δgovernment spending to Δnew EVs registered.

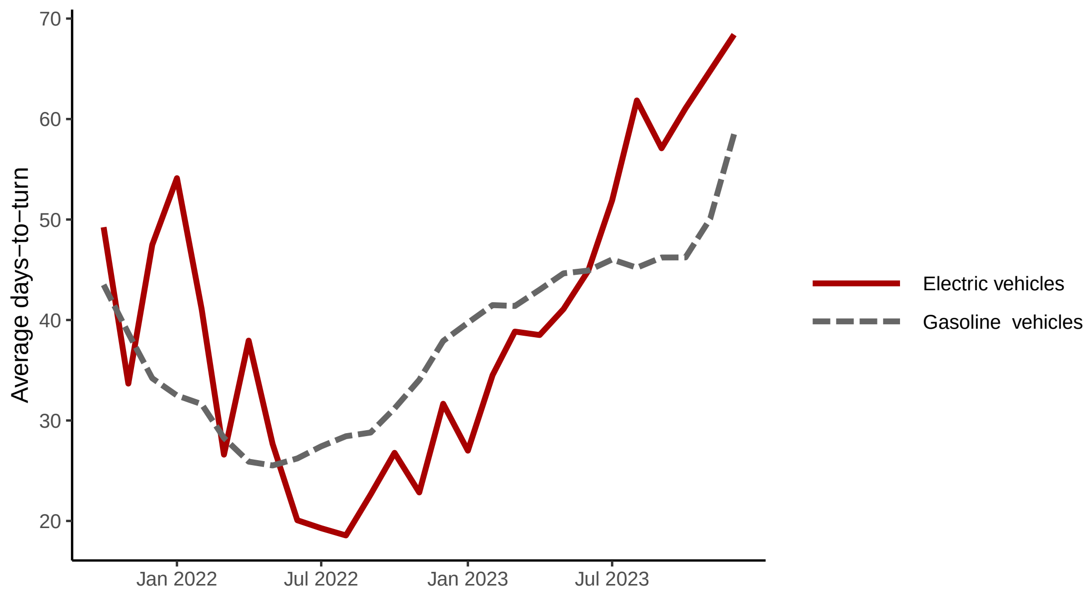
Figure 1: **Section 30D Purchase Credit Eligibility**

Eligibility group	Models	Pre-IRA	8/17/22 - 12/31/22	1/1/23 - 4/17/23	4/18/23 - Late 2023
		Exclude if sales > 200k	Exclude if assembled outside North America	Re-include if sales > 200k; exclude if MSRP > $55k/$80k	Exclude foreign battery minerals/components
Excluded Aug 2022	**Audi** (Q4 e-tron, Q8 e-tron); **BMW** (i4, iX); **Hyundai** (Ioniq 5, Kona); **Kia** (EV6, Niro); **Lexus** (NX PHEV); **Mercedes-Benz** (EQB); **Nissan** (ARIYA); **Polestar** (Polestar 2); **Porsche** (Taycan); **Subaru** (Solterra); **Toyota** (RAV4 PHEV, bZ4X); **Volvo** (C40, XC40, XC60 PHEV, XC90 PHEV)	$7,500			
	BMW (530e PHEV); **Kia** (Sorento PHEV, Sportage PHEV); **Toyota** (Prius PHEV)	$3,750 - $7,500			
Included Jan 2023	**Chevrolet** (Bolt, Bolt EUV); **Tesla** (Model 3, Model Y)			$7,500	
Excluded/reduced Apr 2023	**Ford** (E-Transit, Mustang Mach-E); **Jeep** (Grand Cherokee PHEV, Wrangler PHEV); **Rivian** (R1S, R1T)	$7,500			$3,750
	Ford (Escape PHEV)	$3,750 - $7,500			$3,750
	Audi (Q5 PHEV); **BMW** (X5 PHEV); **Nissan** (Leaf)	$7,500			
Excluded Jan 2023	**Lucid** (Air); **Mercedes-Benz** (EQS)	$7,500			
Always included	**Chrysler** (Pacifica PHEV); **Ford** (F-150 Lightning); **Volkswagen** (ID.4)	$7,500			
Always excluded	**Tesla** (Model S, Model X)				

Notes: This figure shows which models are eligible for the IRA Section 30D purchase credit by time period. The figure includes models averaging more than 300 sales per month in 2022 and 2023. The shading intensity indicates the credit amount that the model is eligible for. The red, blue, and orange colors indicate eligibility changes that we study in Section 5 below. This figure is inspired by Figure 3 of Buckberg (2023). The final column header says "late 2023" because several vehicles were retroactively made eligible in late 2023, and the Tesla Model X became eligible in late 2023 as its MSRP decreased.

Figure 2: **Electric Vehicle Supply Constraints**

(a) **Average Days-to-Turn (Not Including Tesla)**

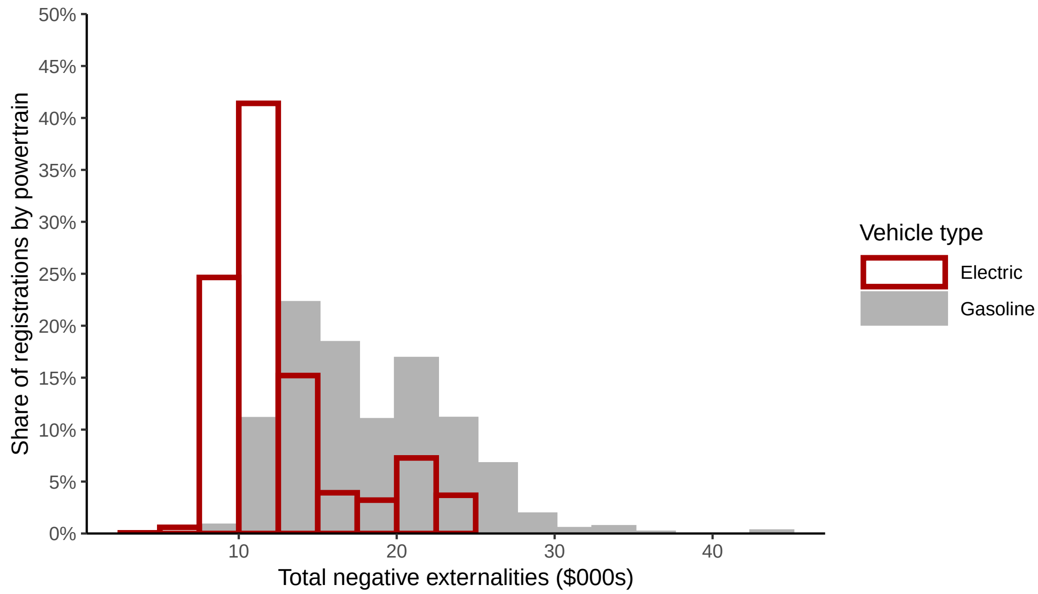


(b) **Tesla Estimated Wait Times**

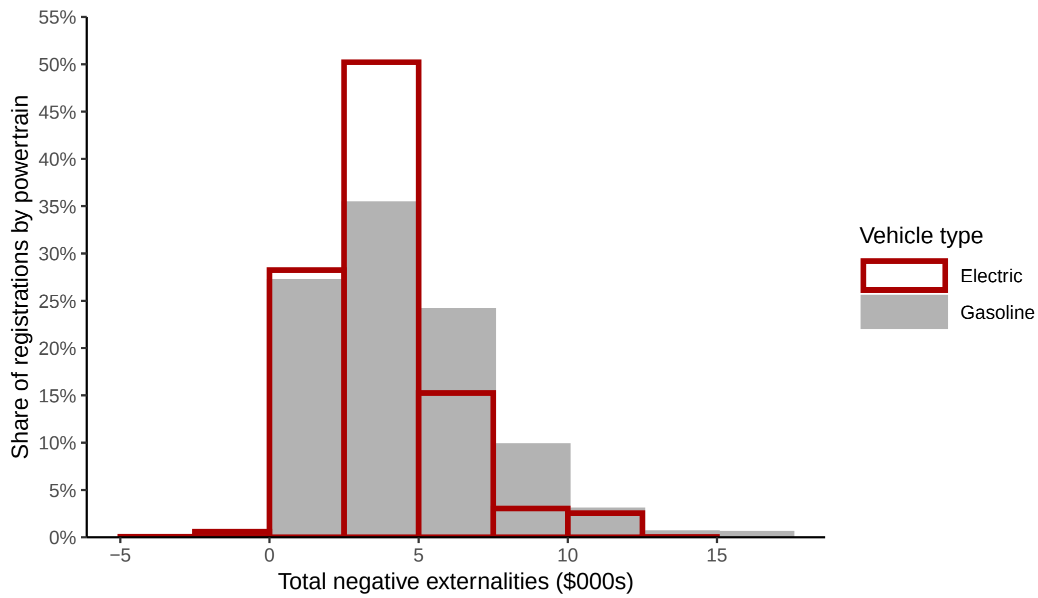
Notes: Panel (a) presents a fixed-weight index of average days-to-turn, i.e., the average time that vehicles sold in that month were available in the dealership's inventory before being sold from Edmunds (2024). The Edmunds data exclude Tesla. Panel (b) presents a fixed-weight index of average delivery wait time reported on the Tesla website (Tesla 2023; Pritchard 2023; The Internet Archive 2023). Both panels present indexes constructed by computing the January 2023 weighted average (weighting models by average monthly sales in months when the model was available), and then recursively adding the sales-weighted average change for all models available in each previous or subsequent month.

Figure 3: **Distribution of Negative Externalities Across Submodels**

(a) **Global SCC**



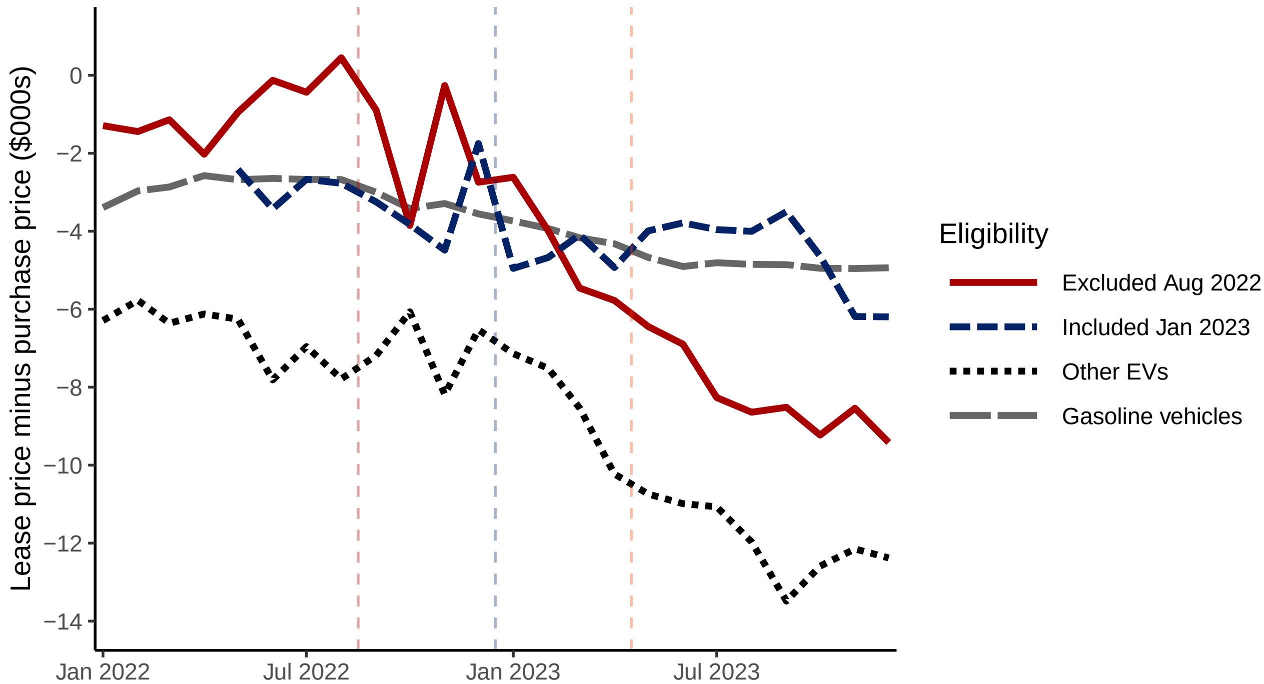
(b) **Domestic SCC**



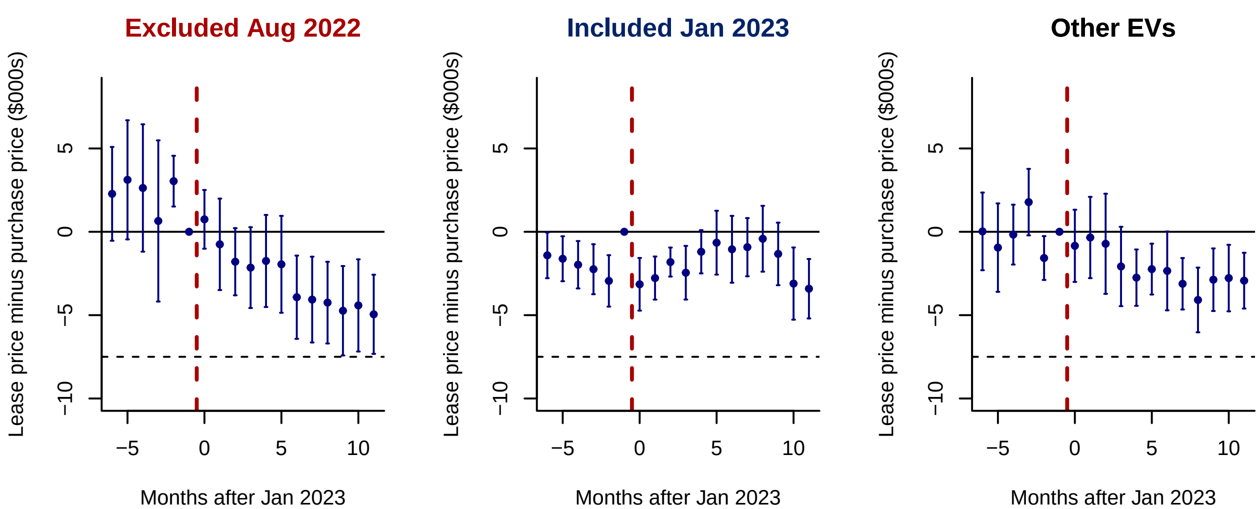
Notes: This figure shows the distribution of total negative externalities across submodels, weighting submodels by registrations in July and August 2023. Carbon damages are evaluated at the global SCC of $241 in panel (a), and at the domestic SCC of $28 in panel (b).

Figure 4: **Relative Lease Price Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



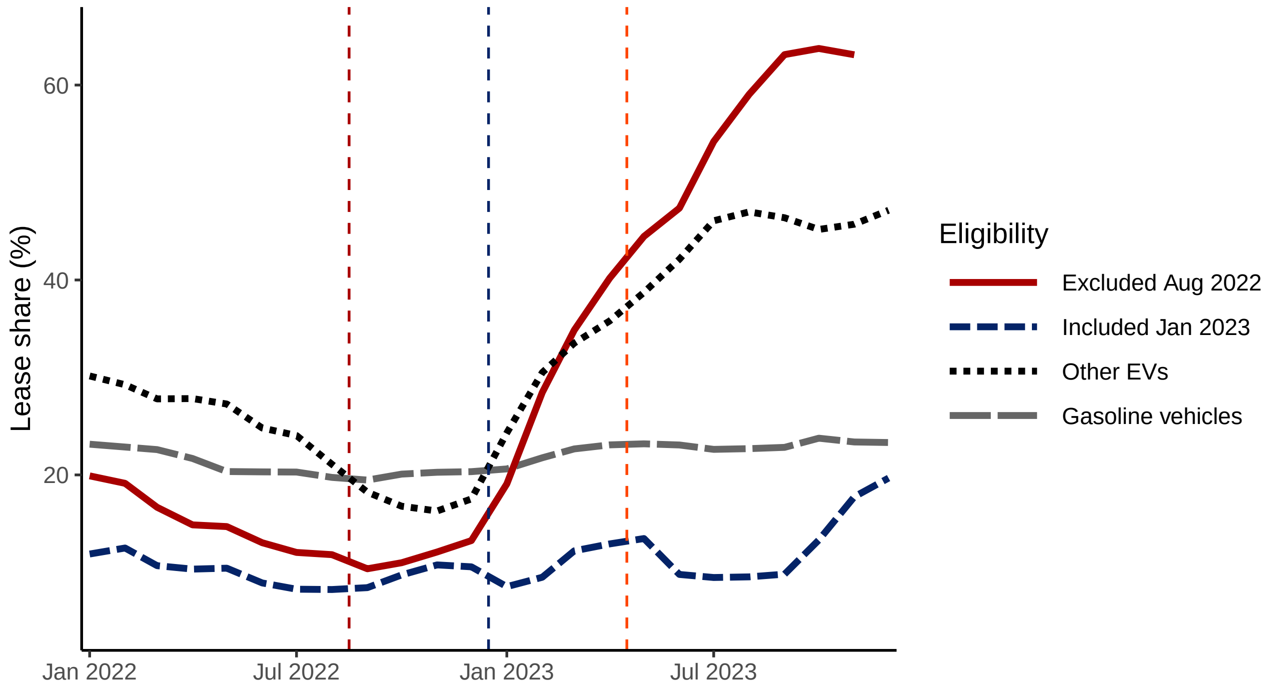
(b) **Event Study Estimates**



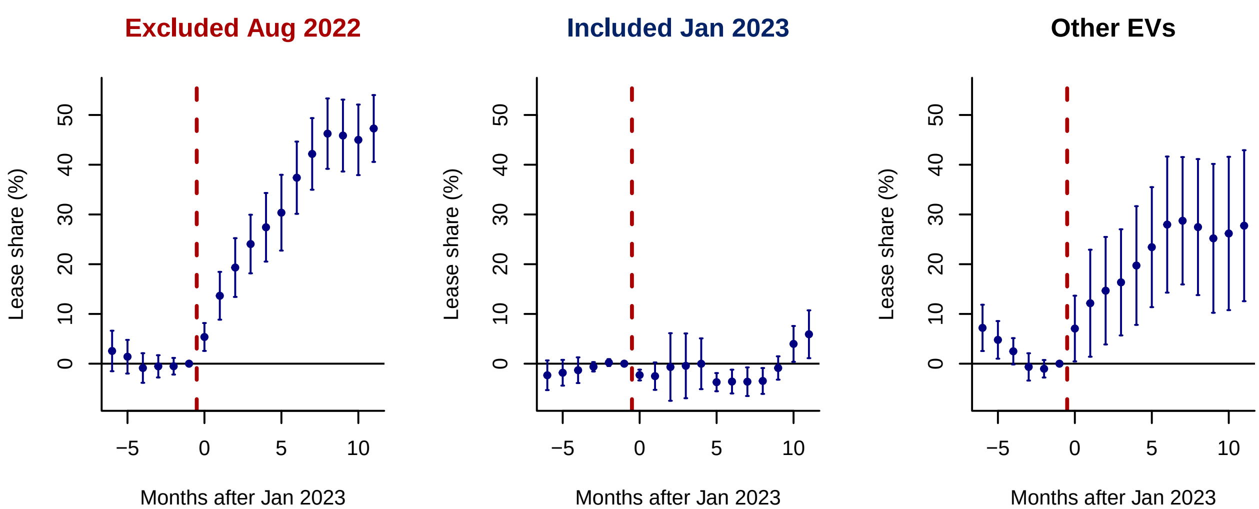
Notes: Panel (a) presents lease price minus purchase price indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1; the Other EVs group includes all EVs not part of either the Excluded August 2023 or the Included January 2023 groups. In both panels, we weight submodels by average monthly sales in months when the submodel was available.

Figure 5: **Lease Share Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**

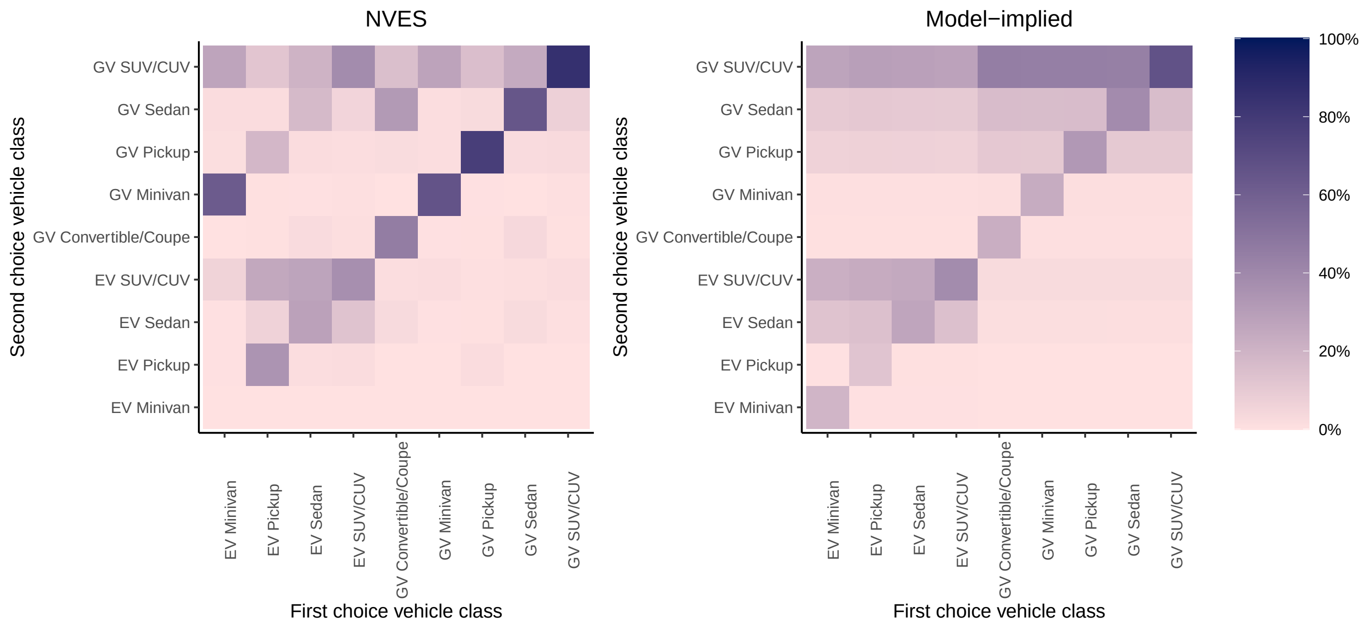


(b) **Event Study Estimates**



Notes: Panel (a) presents lease share indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1; the Other EVs group includes all EVs not part of either the Excluded August 2023 or the Included January 2023 groups. In both panels, we weight submodels by average monthly sales in months when the submodel was available.

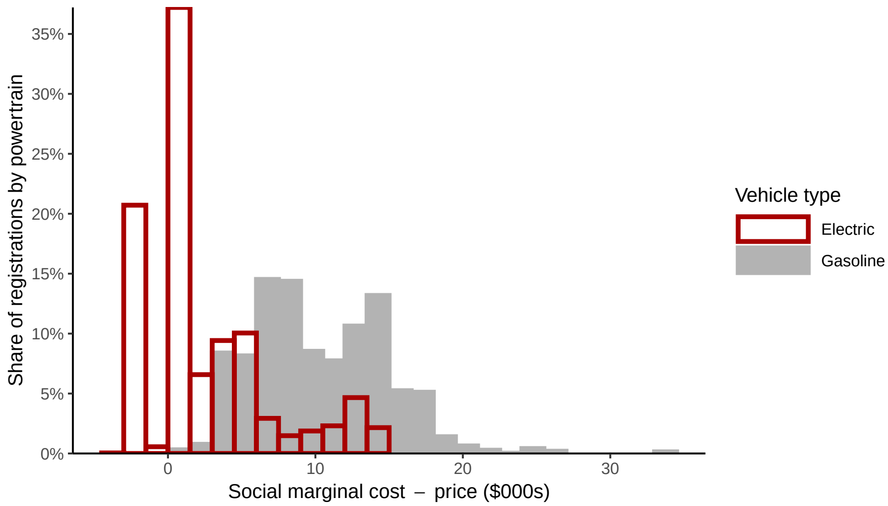
Figure 6: **Heat Map of Second Choices by Vehicle Class**



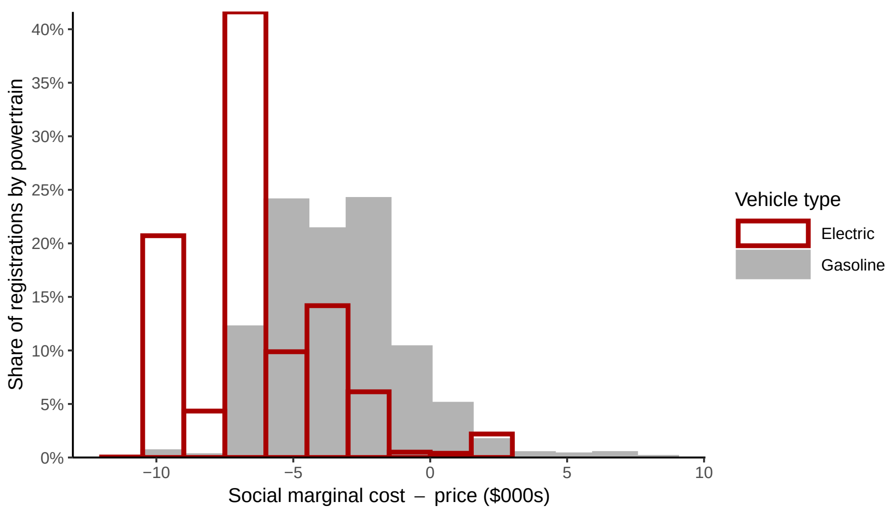
Notes: This figure presents the conditional shares of vehicle class × powertrain second choices; the left panel shows these second choice probabilities from the NVES data, while the right panel shows the model-implied shares. The fact that 0 percent of EV Minivan buyers in the NVES select another EV Minivan as a second choice arises because the NVES aggregates all trims of the Chrysler Pacifica PHEV (the only electric minivan available) with their gasoline counterparts for the second choice survey. Since the minivan segment is a small share of vehicle sales overall, this minimally changes our model fit statistics.

Figure 7: **Distribution of Social Marginal Cost Minus Price Across Submodels**

(a) **Global SCC**



(b) **Domestic SCC**



Notes: This figure shows the distribution across submodels (both purchased and leased) of social marginal cost minus price, weighting submodels by registrations in July and August 2023. Social marginal cost is the inferred marginal production cost c_j plus negative externality ϕ_j; panel (a) computes negative externalities at the global SCC, whereas panel (b) computes negative externalities at the domestic SCC. Price is the unsubsidized market price p_j.

Online Appendix

The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act

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A Data Appendix

A.1 Panel Construction

Our core panel dataset is comprised of data from Experian (quantities), Cox Automotive (lease prices), and the California DMV (purchase prices), together with a collection of supplemental sources.

The Experian data has complete national coverage of new vehicle sales, both purchases and leases, aggregated to the monthly level. To clean these data, we first restrict to considering light-duty vehicles, consider only vehicles purchased for personal use or leased, and exclude fuel cell vehicles. Because vehicle quantities are reported at somewhat different levels of aggregation across observations (e.g. combining similar trims some, but not all of the time), we aggregate to a "lowest common denominator" definition of submodel, which is consistent across observations and across time.

The Cox Automotive data has national coverage, but is not exhaustive as it depends on there being a business relationship between Cox and the firms/dealerships. The dataset is at the transaction level, which allows us to obtain VIN-level information (e.g. assembly location). Additionally, Cox uniquely includes the details of lease contracts, surfacing down payments, monthly payment, and duration. We clean these data by filtering out observations with implausible monthly payments for the vehicles we consider (i.e., below \$200 or above \$1,500) and outlier lease durations (less than 12 months or more than 60 months).

The California DMV data has coverage only for California, and is provided in a sequence of cross-sectional snapshots of currently-registered vehicles. The snapshots we use are from July 2023, October 2023, and April 2024. The variables associated with a registration record include the prefix of the vehicle identification number (VIN), self-reported price, vehicle make, series, model, model year, date of the most recent registration, most recent odometer reading and reading date, year and month of each ownership transfer, and an indicator for whether the vehicle is leased. The VIN prefix is the first 11 digits, excluding the ninth (check digit). We obtain purchase prices from the California DMV data, which combined with lease terms from the Cox data, allows us to compute lease prices which are comparable to directly observed purchase prices. We have also run our analyses using purchase prices from Cox for observations where they are available (approximately 93 percent of registrations in our cross-section) and found similar results, which we do not include in their entirety for the sake of brevity. For comparison, using Cox prices results in counterfactual outcomes which are typically much closer to our baseline specification in column (1) of Appendix Table A6 than any of the other robustness checks.

To transform this sequence of snapshots into a single panel, we employ the following algorithm. First, we check the odometer reading; if it is less than or equal to 250 miles, we use the corresponding odometer reading date as the initial registration date.[39] For vehicles with odometer readings that

[39] In California, the primary registration form for new vehicles (*Form REG-343*) requires reporting the odometer reading "upon date of purchase in California."

are either missing or greater than 250 miles, we then check the latest registration date. Because we observe the model year of the vehicle, we can check whether date is plausibly an initial registration date (i.e., falls between July 1 of the year prior to the model year and April 1 of the year after the model year). If it is, we use the most recent registration date as the initial registration date. If a vehicle doesn't satisfy our requirements for inferring initial registration date on the basis of odometer or latest registration information, we assume we cannot identify the initial registration date for the vehicle, and so drop it from our sample. In practice, 96 percent of initial registration dates in our panel are derived from the first step, using odometer reading/reading date. The remaining 4 percent may be subject to some errors, as California's requirement for annual re-registration of a vehicle could confound successful identification of the initial registration date. For example, a vehicle could be purchased in September of the year before its model year and be re-registered in September of its model year; if this vehicle's observation is also missing a valid odometer reading, or if its ownership was transferred (and hence a new, higher odometer reading was recorded), it would enter our panel as having been initially acquired in September of its model year. We check that our findings are robust to using only the vehicles whose initial registration dates are inferred from their odometer reading.

The main analysis sample makes two other exclusions. We exclude any observations with fewer than 25 registrations. Additionally, we exclude any purchase or lease price observations based on fewer than 10 transactions.

We construct fixed-weight price indices as follows. Define x_{kt} as some variable for submodel k in month t, define $\bar{q}_k$ as submodel mean monthly sales in the months when firms sell it, and define $t = 0$ as January 2023. The fixed-weight index for in month t equals

$$\bar{x}_t = \frac{\sum_k \bar{q}_k x_{k0}}{\sum_k \bar{q}_k} + 1\,(t > 0) \sum_{r=1}^{t} \frac{\sum_k \bar{q}_k \left(x_{k,r} - x_{k,r-1}\right)}{\sum_k \bar{q}_k} + 1\,(t < 0) \sum_{r=-1}^{t} \frac{\sum_k \bar{q}_k \left(x_{k,r} - x_{k,r+1}\right)}{\sum_k \bar{q}_k}.$$

As described in the text, x_{kt} is missing for some kt, so the sums over k implicitly include only non-missing observations. This prevents the computed series from displaying fluctuations entirely driven by panel imbalance.

We check the trend of daily new registration over time based on two cross-sections. We find a delay of roughly 45 days for all registration to appear in the DMV record; that is, the number of observed registrations fall sharply relative to the trend within the 45 days prior to the date the snapshot was taken. Given the possibility that later registrations overwrite earlier ones, we use the earlier cross-section to approximate the initial registration date of earlier-registered vehicles. The final dataset is constructed using the July 2023 cross-section for registrations between August 15, 2022 and April 30, 2023; the October 2023 cross-section for registrations between May 1 and August 30, 2023; and the April 2024 cross-section for registrations between September 1 and December 31, 2023.

In addition to these core data sources, we use the National Highway Traffic Safety Administration (NHTSA)'s VIN decoder to append information on powertrain type (e.g. GV vs. PHEV vs.

BEV) and assembly location. Further combining vehicle names and model years with eligibility information from FuelEconomy.gov, we generate a submodel × month panel, with information on number of monthly registrations (including purchases and leases separately) from Experian, vehicle characteristics including powertrain and assembly location, average recorded purchase price from the California DMV, average lease price and lease price minus purchase price from merging Cox and California DMV data, and credit eligibility. This final merge is achieved by leveraging the presence of VIN-prefix in both the California DMV and Cox datasets, and through a manual crosswalk between vehicle names with Experian.

For Tesla price data, we augment the above panel using the following sources. From Tesla's website, via the Internet Archive's Wayback Machine, we obtain base configuration lease terms and purchase prices for most months in our sample. For those which are inaccessible via the Wayback Machine, we additionally collect price data from contemporaneous reporting courtesy (InsideEVs 2024) and the enthusiast-run project Tesla Car Price History (Bautista 2024). This allows us to consistently compare lease prices and purchase prices for the base configuration of each model across time.

Finally, we used new EV registration data from EV-Volumes to inform our dealership inventory survey (Appendix A.3) and compute market shares to weight the resulting wait times. We also used vehicle registration data from Texas to investigate the frequency of consumers exploiting the "loophole within a loophole" as described in Appendix B.1. These registration data are not as straightforward as those from California's DMV to convert into a panel in part due to a lack of an explicit lease flag, but do feature full vehicle VINs and addresses. These features allow us to track changes in ownership over time, which is crucial for identifying lease buyouts.

For measuring credit eligibility, in the few instances of variation in eligibility within a submodel-by-month, we assign maximal eligibility to all observed transactions. This affects a small number of submodels, such as the BMW 330e (which was being assembled in both Mexico and Germany for the US market in late 2022) and the Volkswagen ID.4 (which moved assembly to Tennessee in late 2022, resulting in some model year 2022 German-assembled ID.4s being registered after the IRA passed).

A.2 Externalities

This subsection provides additional detail on a few components of our estimates of each submodel's externalities.

CO_2 and local air pollution emissions from driving. For EVs, we compute the damages from generating electricity to charge the vehicles, using hourly-seasonalregional short-run marginal emission rates from Holland et al. (2024). These estimates include emissions of CO_2 and of SO_2 and NO_x To aggregate across geographies to the national level, we average across ZIP codes within each state, weighting by each ZIP's total vehicle miles traveled, following Holland et al. (2016), and we average across states weighting by each state's powertrain-specific new vehicle sales in 2023. Since EVs have higher market shares in states with cleaner electricity generation, the state-by-powertrain weighting implies lower marginal damages from EVs than if we assumed that the marginal EVs and GVs had the same sales everywhere.

As a sensitivity analysis, we also consider the impact of estimating carbon emissions from EV charging using the long-run marginal CO_2 emissions estimates from the National Renewable Energy Laboratory’s Cambium “MidCase” scenario, averaged across the estimated values for 2025, 2030, and 2035 (Gagnon et al. 2024). This results in a reduction in CO_2 from charging of 60 percent relative to our baseline numbers (comparing Table A1 to Table 2).

For GVs, we compute the harms from tailpipe emissions. We construct CO_2 emissions using each submodel’s fuel economy rating. We compute submodel-specific local pollution emission factors from US EPA (2024) test data, using submodel-specific certified emission rates for the vehicle’s full useful life as in Jacobsen et al. (2023), combined with regulatory standards. Each submodel’s emissions for each pollutant is computed as the average between the test value and regulatory value. The regulatory standards are likely to over-estimate true emissions, as vehicles over-comply to avoid recalls; the exhaust tests may under-estimate true on-road emissions, as emissions control systems depreciate with age and auto manufacturers optimize vehicle design towards the emissions control test; averaging the two provides a middle-ground. Using these emissions rates, we again compute the weighted average marginal damage across ZIP codes using marginal damage estimates for local pollutants from the AP3 integrated assessment model (Clay et al. 2019). We assume that 63 percent of PHEV miles traveled are on gasoline and 37 percent are on electricity, following Plötz et al. (2020).

We calculate the US SCC by taking the ratio of the US to global SCC in Ricke et al. (2018), averaging across models and scenarios, then multiplied by our CPI-inflated global SCC value.

Accident externalities. Following Anderson and Auffhammer (2014), we estimate the expected increased mortality cost from accidents of each submodel relative to the lightest vehicle available. The mortality cost is the product of the accident probability, the incremental death probability from driving a heavier vehicle, and the value of a statistical life (VSL). Our estimate of the accident probability comes from dividing the total number of vehicles involved in multi-vehicle accidents by the number of unique vehicles on the road between 2004 and 2021. An alternative calculation, which estimates the probability of a vehicle being in a multi-vehicle accident by a regression of accident counts on registered vehicles, agrees empirically with the first approach when we disregard the possibility of the same accident being in more than one multi-vehicle accidents over its lifetime. We use the estimate obtained from the first method, 27 percent, and follow Anderson and Auffhammer (2014) for the remainder of the calculation.

Positive fiscal externalities. For EVs, we use the utility-specific markups on residential electricity above private marginal cost calculated by Borenstein and Bushnell (2022), weighting utilities within a state by sales and weighting states by new EV sales in 2023. The resulting weighted average markup is 12 cents per kWh. For GVs, we use federal and state gas taxes, weighting states by new GV sales in 2023. The resulting weighted average gas tax is 55 cents per gallon. A submodel’s total positive fiscal externality depends on those markup or tax amounts and the submodel’s electricity use or fuel economy.

A.3 Dealership Inventory Survey

Between July 7 and August 4, 2023, we conducted a survey targeting dealerships selling popular EVs in a number of geographically diverse markets with relatively large EV adoption rates. We collected responses from the West Coast (Los Angeles, San Diego, San Jose, and San Francisco), East Coast (New York and Philadelphia), the Midwest (Minneapolis), and the South (Houston). These are in addition to a brief pilot, whose results are unreported here, conducted in St. Louis in early July prior to the other surveys.

We compiled a list, from EV-Volumes data, of the EV models that were most popular in 2022 and early 2023. Some vehicles were omitted due to having been discontinued by the time of our survey, and others were omitted due to being largely or entirely sold direct-to-consumer (namely Rivian and Tesla). RAs then searched for dealerships selling each make, and contacted them by phone. For each model, they then asked

> Hello, my name is ____ and I’m interested in purchasing a [*model name*]. I would be paying cash for the vehicle. When would be a feasible delivery time for the vehicle? How much should I expect to pay? How about delivery times for your other electric or plug-in hybrid vehicles?

The RAs then recorded this information for each of the EV models which the dealership in question sold. If the model was not in stock up to two more dealerships were contacted in the city; our analysis is conducted on the minimum wait time across contacted dealerships in the city. Additional information concerning the exact trim and sales price were recorded, though are not directly used here; we did not observe systematic markups relative to MSRP. In total, we recorded wait times for a total of 681dealership-model combinations.

For each dealership-model combination with non-zero wait time, we assign the midpoint of the predicted window given as that dealership-model wait time. We then take the minimum of these within cities to obtain a city-model dataset. These data are merged with EV-Volumes registration records from July and August, and we compute the proportion of wait times that are zero days, within 30 days, and within 60 days both weighted (by national market share) and unweighted.

A.4 Employment Intensity

To compute the domestic employment effects of vehicle production, we partition the automotive production sector into two components: final assembly and parts. Cuenca, Gaines, and Vyas (1999) estimate that parts account for $\sim 80\%$ of total costs and final assembly for ~ 20.[40] We then

[40] We considered obtaining these statistics from input-output tables but chose not to for a few reasons. Specifically, we examined the cost structure of the automobile manufacturing industry (NAICS code 336111) in the 2017 Use table after redefinitions at producer prices from the Bureau of Economic Analysis. The partition of intermediate goods into “automotive parts”’ and other industries in the Use table is likely prone to measurement error. The

compute number of US workers in the final assembly and parts manufacturing according to the following formulas:

$$l_j^{\mathrm{a}} = \frac{c_j \times \mathrm{US}_j^{\mathrm{a}} \times 0.2 \times \mathrm{r}^{\mathrm{a}}}{w^{\mathrm{a}}} \text{ and } l_j^{\mathrm{p}} = \frac{c_j \times \mathrm{NA}_j^{\mathrm{p}} \times 0.8 \times \mathrm{r}^{\mathrm{p}}}{w^{\mathrm{p}}}$$

Using these values, we calculate the following baseline aggregates:

$$L^{\mathrm{a}} = 6 \times \sum_j R_j l_j^{\mathrm{a}} \approx 103,000 \text{ and } L^{\mathrm{p}} = 6 \times \sum_j R_j l_j^{\mathrm{p}} \approx 236,000$$

Here l_j^{a} and l_j^{p} represent the per-vehicle number of US workers associated with the production of submodel j in the assembly and parts industries, respectively. From our model, we take submodel-specific estimates of per-vehicle production costs c_j. We use ancillary data on the share US_j^a of submodel j assembled in the US, and the share NA_j^p of submodel j parts from the US or Canada. For assembly, we calculate the ratio of payroll to value added r^{a} for assembly, and the ratio of payroll to output r^{p} for parts. We divide these by the mean wages w^{a} and w^{p} of workers in the assembly and parts industries, respectively. To calculate the baseline aggregates, we use data on registrations R_j of each submodel in our two-month panel. We use the share of payroll in value added in the assembly industry since we interpret the 20 percent share as representing the value added from the final assembly process beyond the value of the input parts, abstracting from intermediates besides auto parts. We use the share of payroll in output for the parts industry since the 80 percent share is from the perspective of the final assembler, while expenditures on parts are revenue from the perspective of firms in the parts industry. The aggregate employment figures are calculated analogously across the counterfactual scenarios we consider, and we then compute the change in employment in each industry relative to the baseline under the IRA.

The aggregate employment figures produced by summing up our employment measures (that is, L^{a} and L^{p}) differ from industry-wide aggregates for a few reasons; the BLS reports employment of 254,000 and 618,000, respectively, in the final assembly and parts industries. First, our construction captures only employment associated with vehicles which are purchased or leased domestically. for this reason, final vehicles which are exported (accounting for approximately 15 percent of production according to total production as reported by International Organization of Motor Vehicle Manufacturers (2023) and exports reported by US International Trade Administration (2025) and parts which are exported for assembly into vehicles purchased outside of the US are counted in simple aggregate employment figures but are intentionally excluded from our calculations. Within the parts industry specifically, some portion of the industry's output is used for purposes other than producing new vehicles (e.g. replacement and aftermarket parts). Additionally, our registration data cover only a subset of the overall light-duty vehicle market; while we capture the vast

auto parts industry (4-digit NAICS code 3363) accounts for over half of all intermediate goods that the automobile manufacturing industry purchases. The largest other suppliers of intermediate goods to auto manufacturing industries include retail, wholesale, engines, glassware, unspecified machinery, etc., and other industries that are likely supplying auto parts. Additionally, the Use table does not distinguish EV versus GV manufacturing, and EV manufacturing was even less common in 2017.

majority (over 80 percent) of non-commercial light-duty registrations (our panel, once annualized by multiplying by six, counts 10.74 million registrations as compared to the true value of 12.95 million), there are an additional 2.5 million fleet sales which we exclude from our analysis (National Automobile Dealers Association 2023). Finally, we suspect that the fleet vehicles may be disproportionately US-made, in which case our aggregate employment estimates would undershoot relative to industry totals.

B Descriptive Facts Appendix

B.1 Texas Registration Data Analysis

To examine the frequency with which EV buyers took advantage of the "loophole within a loophole" (that is, first leasing a vehicle ineligible for the purchase credit, obtaining advantageous lease terms due to the leasing loophole, then proceeding to buy out the lease), we combined two data sources with VIN-level information. The first is Cox Automotive's data on new vehicle transactions, which allows us to identify VINs associated with leases. The second is Texas registration data, which allows us to track the same VIN across time (as we can observe repeated registrations for the same VIN). This is not possible using the California data, which is provided at the VIN-prefix level. Because the California registration data lack the full VIN to identify a particular vehicle across time, they do not let us identify lease buyouts in California. On the other hand, the Cox data alone does not have information on re-registrations of vehicles or of lease buyouts directly. We also note that, while the Texas market is not as large as California's, it is the second largest in the country and makes up a substantial share of the US market.

Combining the Cox and Texas registration data, we computed the early buyout rate in Texas by filtering to vehicles which were recorded as leased in the Cox data and identifying vehicles that were re-registered to a different address within three months of their initial registration. We use the three month window given the comments dealerships conveyed about rapidly converting a lease to a purchase for consumers who hoped to purchase a vehicle but obtain the lease subsidy. We use re-registration as a proxy for buyouts, as leased vehicles appear to be almost exclusively recorded as being initially registered to a leasing company; in our data, over 90% of leases are initially registered to addresses with at least 100 leased vehicles over the time period. These addresses are either out-of-state, P.O. boxes, or known addresses of leasing companies.

This analysis finds that levels of estimated early buyouts remained low among EVs and GVs both before and after the new lease credit rules went into effect. In late 2022, EVs and GVs had early buyout rates of around half a percent of leases. In early 2023 EVs had an early buyout rate of around 1.4 percent. The estimated GV early buyout rate remained unchanged.

C Event Study Appendix

C.1 Event Study Regression Tables

Table A2 presents the regression estimates used in the calibration of the empirical model in Section 6. Table A3 presents regression estimates documenting the lack of substantial price changes after EVs lost eligibility in August 2022 and April 2023.

C.2 Doubly-Robust Event Studies

This appendix presents “doubly robust” estimates where the GV control group is reweighted to match the EV pre-IRA average price. We compute weights with entropy balancing (Hainmueller 2012). This method computes weights such that the reweighted sample matches a set of target moments, while maintaining maximal “closeness” (in an entropy sense) to a set of researcher-defined initial weights. In our case, these initial weights are the monthly average registrations of each GV, and the targeted moment will be average pre-IRA purchase price. Since EVs have a higher average price, this will have the effect of upweighting more expensive GVs.

Because we can only compute new weights for GVs which are present in the pre-period sample, we lose a little less than 5 percent of overall registrations after switching to these weights. To ensure that the aggregate EV-GV balance is approximately the same between the primary specification and this alternative specification, the entropy-balanced weights are normalized to sum to one, then multiplied by the monthly average registrations across all GVs.

Appendix Figures A10–A12 present the reweighted event study estimates.

C.3 Event Studies with Registration Quantities and Purchase Prices

This appendix presents event studies of changes in purchase prices and in total registrations (including both purchases and leases) around the 30D vehicle eligibility changes. Purchase prices are discussed in more detail in Section 5.2, and so we focus here on interpreting results for quantities. The IRA should affect total registrations in several ways. First, changes in vehicle eligibility for Section 30D credits should shift demand among income-eligible consumers. Second, the January 2023 income eligibility restriction for Section 30D credits should reduce EV demand among consumers who do not want to lease. Third, the January 2023 availability of EV lease credits under 45W should increase overall EV demand.

The fixed-weight purchase price indices in Panel (a) of Appendix Figure A13 suggest limited changes in purchase prices coincident with credit eligibility. The red and orange vertical lines indicate the date of eligibility change for the eligibility group of the corresponding color from Figure 1. For the vehicles that lost credit eligibility in August 2022, shown in red, prices change relatively little in the several months before and after those vehicles lost eligibility in mid-August 2022, although prices drop more substantially in early 2023 as part of the price cuts described in Figure A1. For the Excluded/Reduced April 2023 group in orange, prices also drop temporarily in early 2023, but the index stays in the range of \$63,000 to \$65,000. For all other EVs in black, which is mostly Tesla, prices drop by more than \$10,000 between mid-2022 and the end of 2023. The price trends in late 2022 may reflect supply conditions, while we interpret patterns in Spring and Summer 2023 as less constrained.

The event study coefficients γ_s^e from equation (2) for each eligibility group in Panel (b) of Appendix Figure A13 corroborate this finding, as they also suggest limited effects from 30D credit eligibility changes on purchase prices. The confidence intervals rule out price drops of more than \$500 to \$1,000 between September and December 2022 among the vehicles excluded from credit eligibility in August 2022. They also rule out price drops more than \$2,000 among the group of vehicles that lost or had decreased credit eligibility in April 2023. We do not consider event studies for the groups that changed eligibility in January 2023 because those coincide with the large Tesla-led price cuts, reflecting broader contemporaneous market trends. Regression estimates that restrict the coefficients to be equal across the submodels that experienced an eligibility change in August 2022 and April 2023 also suggest that prices did not substantially fall following these eligibility changes. These estimates reject the hypothesis that prices dropped by more than \$620 in the three months after losing eligibility versus the three months before; see Appendix Table A3.

Appendix Figure A14 presents the fixed-weight indexes and event study estimates. The figures illustrate substantial market trends that predate, and are thus likely unrelated to, changes in EV credit eligibility. The Excluded August 2022 group saw a significant registration decrease in July and August 2022 (before they lost 30D eligibility), driven by decreases for Hyundai and Kia. The Included January 2023 group saw a steady increase in 2022 and 2023 (before they regained 30D eligibility), as Tesla demand grew steadily. The Excluded/Reduced April 2023 group saw decreases in registrations in the first few months of 2023 (again, before they lost 30D eligibility).

Comparing against the final month before the eligibility change (month -1 on the x-axis), the figures show no statistically detectable evidence of responses to credit eligibility. For the Excluded August 2022 group, the 95 percent confidence intervals rule out registration decreases of more than about 20 percent. For the Included January 2023 group, the confidence intervals rule out registration increases of more than about 20-30 percent. For the Excluded/Reduced April 2023 group, the confidence intervals rule out registration decreases of more than about 20-30 percent in the ensuing four months. However, especially given the evidence of other market trends before the eligibility changes, we do not know what would have happened but for those eligibility changes.

Relative Lease Prices

Panel (a) of Figure 4 presents the fixed-weight indexes of relative lease price for the two groups of EVs that changed eligibility, all other EVs, and all GVs. Relative lease price for GVs dropped moderately in both 2022 and 2023. As the market weakened, relative lease prices for EVs also decreased in the latter half of 2022. For the Excluded August 2022 group, lease prices decreased more sharply in 2023. For the Included Jan 2023 group, relative lease prices increased temporarily in December 2022, because Tesla cut purchase prices in that month but did not correspondingly cut lease prices until the next month. The group's relative lease prices were relatively flat in 2023 until Tesla started to offer a $7,500 lease rebate late in the year, and the blue line correspondingly drops in November and December 2023. For all other EVs, relative lease prices also decrease more than those of GVs over the course of 2023.

Panel (b) of Figure 4 presents the event study estimates. We define the "event" as the start of 45W lease credits in January 2023. The patterns match Panel (a), except that they adjust for the comparison to GVs, where relative lease prices also decreased. The left sub-panel shows that for the Excluded August 2022 group compared to GVs, relative lease prices decreased by about $5,000 compared to December 2022, and by about $7,000 relative to their level in July through November 2022. The middle sub-panel shows that with the exception of the December 2022 blip, the Included Jan 2023 group relative lease prices trended slightly upward relative to GVs during 2023 until the November 2023 Tesla lease price reduction. The right sub-panel shows that for all other EVs, relative lease prices dropped by around $3,000 relative to GVs by the end of 2023.

Also notable is the heterogeneity in EV relative lease price changes across firms; see Appendix Figure A8. By July-August 2023 relative to October-December 2022, Kia, Volvo, Volkswagen, and Hyundai had dropped relative lease prices by about $7,500, Jeep, BMW, Toyota, and Ford had dropped relative lease prices by about $1,000 to $4,000, and Tesla and GM had not reduced relative lease prices.

While the Excluded August 2022 group's relative lease price decrease in 2023 is consistent with substantial or full pass-through of the $7,500 lease credit, two other results are not. First, while Tesla eventually offered lease rebates, the Tesla and GM relative lease price decreased by much less than $7,500, and the decrease only occurred after an 11-month delay. Second, the Excluded August 2022 group's relative lease price did not increase in late 2022 after losing eligibility. An industry insider suggested a possible explanation—the IRA might have caused a change in economic incidence. Perhaps the lease credit was not passed through before the IRA, but media coverage of tax credits and the leasing loophole could have raised the salience of leasing and the tax credit, inducing firms to compete harder for leases.

Comparison to Model

The equilibrium model does not target the observed pass-through of credits to prices from Section 5, but the simulated pass-through in the model following the removal of all EV credits indicates that they are reasonably aligned. First, as a comparison to the purchase price patterns in Figure A13 Panel (b), we look at pass-through of credits to purchase prices. Among EVs that previously had credits, the model indicates that purchase prices fall by only $476 on average, suggesting that the incidence of the purchase credits mostly falls on consumers, consistent with our descriptive findings. Second, as a comparison to the lease price patterns in Figure 4 Panel (b, left), we look at pass-through of credits to lease prices (relative to purchase prices). Among EVs in the same Excluded August 2022 group, the model indicates more than complete pass-through of $8,022 to consumers, overshifting by 7.5 percent above the $7,500 amount. The fact that our model is able to generate overshifting is a consequence of the consumer heterogeneity in our model, which leads to more flexible demand curvature (Miravete, Seim, and Thurk 2023). Of course the regressions and model could differ for many reasons, most notably supply chain conditions in the pre-IRA period.

D Equilibrium Model

D.1 Quantity Demanded and Consumer Surplus

There are M consumers in the market indexed by i. We define consumer types $h(i)$ with representative income $y_{h(i)}$, with a continuum of consumers receiving indirect utility from choice j with price p_j and demand subsidy, if income-eligible, $\tau_{h(i)j}$ equal to

$$U_{ih(i)j} = \xi_j - \alpha_{h(i)} \left(p_j - \tau_{h(i)j}\right) + \boldsymbol{\beta}^{'}_{h(i)} \boldsymbol{X}_j + \epsilon_{ij}$$

where ξ_j is a common consumption utility common to all consumers and ϵ_{ij} is an idiosyncratic preference unique to each consumer distributed type-1 extreme value (mean zero and unit scale). In the nested logit, each ϵ_{ij} draw is independent across individuals but, for a given individual, is correlated across nests as in equation (4). We normalize the common part of utility of the outside option to zero, so $U_{i0} = \epsilon_{i0}$. Consumers have heterogeneous price sensitivities and preferences for specific vehicle attributes in $\boldsymbol{X}_j$ across types according to $\alpha_{h(i)}$ and $\boldsymbol{\beta}^{'}_{h(i)}$. Specifically,

$$\begin{aligned} \alpha_{h(i)} &= \exp(\alpha_0 + \alpha_y y_{h(i)}) \\ \boldsymbol{\beta}^{'}_{h(i)} \boldsymbol{X}_j &= (\beta_0 \times 1_j\{\text{Inside good}\} + \beta_{EV} \times 1_j\{\text{EV}\} + \beta_{Lease} \times 1_j\{Lease\}) \times y_{h(i)} \end{aligned}$$

Integrating over consumers of a given type h, the market share of choice j is

$$s_j^h = \int 1\{U_{ihj} \geq \max_{k \in \mathcal{J}} U_{ihk}\} dF(\boldsymbol{\epsilon_i})$$

To express the market shares of each choice under the nested logit assumption for $F(\cdot)$, it is useful to first define the following inclusive values, which represent the expected utility of a choice within a nest conditional on selecting that nest

$$\begin{aligned} I_k^h &= (1 - \sigma^k) \ln \sum_{j \in \mathcal{J}_k} \exp\left(\frac{\xi_j - \alpha_h \left(p_j - \tau_{hj}\right) + \boldsymbol{\beta}^{'}_h \boldsymbol{X}_j}{1 - \sigma^k}\right) \\ I_c^h &= (1 - \sigma^c) \ln \sum_{k \in \mathcal{K}_c} \exp\left(\frac{I_k^h}{1 - \sigma^c}\right) \\ I_g^h &= (1 - \sigma^g) \ln \sum_{c \in \mathcal{C}_g} \exp\left(\frac{I_c^h}{1 - \sigma^g}\right) \\ I^h &= \ln\left(1 + \sum_{g \in EV,GV} \exp I_g^h\right) \end{aligned} \tag{13}$$

In the above notation, $\mathcal{J}$ is the set of (1359) options available to purchase or lease, plus the outside option; $\mathcal{J}_k$ is the partition of $\mathcal{J}$ corresponding to submodel k in the set of (759) submodels $\mathcal{K}$, plus the outside option; $\mathcal{K}_c$ is the partition of $\mathcal{K}$ corresponding to class c in the set of (9) classes

$\mathcal{C}$, plus the outside option; and $\mathcal{C}_g$ is the partition of $\mathcal{C}$ corresponding to powertrain $g \in \{\text{EV,GV}\}$, plus the outside option. Our normalization of the mean outside option value to zero and placement of the outside option in a nest all by itself implies that in each of the first three lines, $I_{h0} = 0$. This is the source of the 1 in the final inclusive value.

Then, unconditional choice probabilities for j are given by the product of conditional probabilities within a nest and the overall choice probability of powertrain, g, which can in turn be expressed in terms of the inclusive values above:

$$\begin{aligned} s_j^h &= s_{j|k(j)}^h \times s_{k(j)|c(j)}^h \times s_{c(j)|g(j)}^h \times s_{g(j)}^h \\ &= \frac{\exp\left(\frac{\xi_j - \alpha_h\left(p_j - \tau_{hj}\right) + \boldsymbol{\beta}_h' \boldsymbol{X}_j}{1-\sigma^k}\right)}{\exp\left(\frac{I_{k(j)}^h}{1-\sigma^k}\right)} \times \frac{\exp\left(\frac{I_{k(j)}^h}{1-\sigma^c}\right)}{\exp\left(\frac{I_{c(j)}^h}{1-\sigma^c}\right)} \times \frac{\exp\left(\frac{I_{c(j)}^h}{1-\sigma^g}\right)}{\exp\left(\frac{I_{g(j)}^h}{1-\sigma^g}\right)} \times \frac{\exp I_{g(j)}^h}{\exp I^h} \end{aligned} \tag{14}$$

McFadden (1978) provides a full derivation given the joint CDF of ϵ_{ij}. Total registrations come from aggregating these within-type market shares, given each type is a share w_h of the total population of M consumers

$$q_j = M \sum_h w_h s_j^h$$

The substitution between any two choices,j and r, given by $\frac{\partial q_j}{\partial p_r}$ in equation (6), can be derived using equations (13) and (14).

In the nested logit extension to the Small and Rosen (1981) log-sum consumer surplus formula, total consumer surplus is given by

$$CS = \sum_h w_h \frac{I^h}{\alpha_h} \tag{15}$$

D.2 Estimation

The demand side parameters are estimated using a nested fixed-point approach: the outer loop uses a gradient-based optimization over the eight structural parameters $\boldsymbol{\alpha} = \{\alpha_0, \alpha_y\}$, $\boldsymbol{\beta} = \{\beta_0, \beta_{EV}, \beta_{Lease}\}$, and $\boldsymbol{\sigma} = \left\{\sigma^k, \sigma^c, \sigma^g\right\}$ to match our eight data moments while the inner loop solves for $\boldsymbol{\xi}$ using the Berry (1994) contraction mapping to match observed market shares. The contraction mapping is adapted to the nested logit using Grigolon and Verboven (2014), who show that the contraction at each iteration (t) must be dampened by $1 - \max\left\{\sigma^k, \sigma^c, \sigma^g\right\}$

$$\xi_j^{(t+1)} \hookleftarrow \xi_j^{(t)} + \left(1 - \max\left\{\sigma^k, \sigma^c, \sigma^g\right\}\right)\left(\log s_j^{obs} - \log s_j^{(t)}\right) \tag{16}$$

where s_j^{obs} are observed market shares in the data and $s_j^{(t)}$ are implied market shares in the model given prices and the current values of outer loop parameters and $\xi_j^{(t)}$. In the outer loop, we minimize the L^2-norm between our model moments, $m_n(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma})$, and our estimated data moments,

$\hat{m}_n$, $n = 1, ..., 8$

$$(\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\beta}}, \hat{\boldsymbol{\sigma}}) = \arg\min Q(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}) = \sqrt{\sum_n \left(m_n(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\sigma}) - \hat{m}_n\right)^2} \tag{17}$$

The eight moments we match are (1) a market share-weighted model-level own-price demand elasticity, (2) the change in lease shares from a simulated increase in lease prices for the subset of vehicles excluded from credits in August 2022, (3) the share of EV owners who choose another EV as a second choice if their first choice was unavailable, (4) the share of EV owners who would choose another EV in the same vehicle segment as their first choice if their first choice was unavailable, (5) the difference in average transaction price for high- and low-income households, (6) the difference in EV choice shares for high- and low-income households, (7) the difference in lease choice shares for high- and low-income households, and (8) the ratio of inside choice shares for high- to low-income households. Since we have as many moments as parameters to estimate, we match the targeted moments exactly.

The values of each data moment and their source is present in Table 4. For the own-price elasticity, since our model is at the level of a submodel-by-purchase option while the data elasticity moment is aggregated to the model-level, we simulate the model-level elasticity by raising and lowering prices by 0.5 percent and taking the average percent change in registrations as a central difference approximation. We do this for every model and take a registration-weighted average. For simulating the lease share change, we raise the price of the purchase options for the August 2022 excluded group and calculate the new choice probabilities for each option. We compute the change in the share of registrations for each submodel that are leases and then compare the registration-weighted average change in lease shares across submodels.

To calculate the second choice moments in the model, we simulate removing each submodel k from the choice set and compute the new choice probabilities for all remaining products. Define $s_{r\backslash k}$ as the market share of submodel r when k is unavailable. The second choice share is defined by the ratio

$$\frac{s_{r\backslash k} - s_r}{s_k} \tag{18}$$

since any new registrations of r when k is no longer available must be from consumers who originally had k but then had r as their next best option. The NVES only surveys consumers who registered a new vehicle and we can only compute second choice shares among respondents who provided one, so in practice we actually compute $s_{r\backslash k,0}$ for $r, k = 1, ..., K$, where $\backslash k, 0$ removes k and the outside option from the choice set.[41] The share of EV consumers whose second choice is also an EV is then given by

$$D_{EV\to EV} = \frac{\sum_{k\in EV} s_{k\backslash 0} \left(\sum_{r\in EV} s_{r\backslash k,0}\right)}{\sum_{k\in EV} s_{k\backslash 0}} \tag{19}$$

[41] The proportional substitution in the nested logit to the outside option implies $s_{k\backslash 0} = s_k/(1 - s_0)$. Over half of respondents (58.5 percent) did not consider a second choice.

Similarly, the own-class share among EV owners is given by a weighted average across classes, c, within EVs:

$$D_{EV-class \to EV-class} = \frac{\sum_{c \in EV} s_{c\backslash 0} \left(\frac{\sum_{k \in c} s_{k\backslash 0} \left(\sum_{r \in c} s_{r \backslash k, 0} \right)}{\sum_{k \in c} s_{k \backslash 0}} \right)}{\sum_{c \in EV} s_{c \backslash 0}} \tag{20}$$

The differences in transaction prices, lease propensity, EV propensity, and the inside choice ratio for high- versus low-income households are computed by calculating the type-specific values and aggregating over types according to their share of the total vehicle market. To compute the inside choice share in the survey data, we combine the NVES data with information about the population distribution from the IRS SOI. Using the provided survey weights, which are meant to reflect the composition of the overall new vehicle market, we compute aggregate vehicle sales among high- and low-income households in the NVES and divide that number by the count of households in the IRS SOI data. This gives us an estimate of the average number of vehicles acquired per household. The ratio of that statistic between households above and below \$300,000 of reported income measures differences in inside choice propensities.

While we only target the overall difference between high- and low-income households, Figure 6 reports that we closely match overall patterns across the full income distribution.

Estimation of the supply side consists of inverting the Nash-Bertrand first-order condition in equation (8). In particular, stacking the system of J equations gives the markup equation

$$\boldsymbol{\mu} = -\tilde{\boldsymbol{\Omega}}^{-1} \boldsymbol{q} \tag{21}$$

where $\boldsymbol{\mu}$ is a J-vector of markups, $\mu_j = p_j - c_j + \kappa_j$ and $\tilde{\boldsymbol{\Omega}} = \boldsymbol{\Omega} \odot \mathcal{H}$ is the matrix of demand derivatives multiplied (Hadamard product) by the firm ownership matrix. That is, if $f(j)$ returns the identity of the firm that produces j, then each j, r element is given by $\left[\tilde{\boldsymbol{\Omega}}_{jr}\right] = \frac{\partial q_r}{\partial p_j} \times 1_{f(r)=f(j)}$. Given, the estimated demand parameters, we can compute $\tilde{\boldsymbol{\Omega}}$ and $\boldsymbol{q}$ to back out markups and—given prices and subsidies—marginal costs.

To compute alternative price equilibria in our counterfactuals that change the policy vectors $\boldsymbol{\tau}$ and $\boldsymbol{\kappa}$, we take our estimated marginal costs and demand parameters as given and then follow the standard approach found in Morrow and Skerlos (2011) to solve a fixed-point problem closely related to equation (21). The solution to that equation coincides at an equilibrium point. As discussed in Section 6, there is no guarantee that the pricing equilibrium will be unique, but we do not encounter multiple equilibria in practice. Figure A17 presents the distribution of implied marginal costs in the first panel, and the distribution of equilibrium markups under a counterfactual policy environment with no EV subsidies.

D.3 Computation of Standard Errors and Confidence Intervals

We compute the asymptotic variance of our model parameters using the delta method. Call $\theta \in \mathbb{R}^P$ the P-vector of model parameters to estimate. The model-implied moments, $m(\theta; z)$ are a function of these parameters and other data inputs, $z \in \mathbb{R}^Z$. In our main specification, $P = 8$ and $Z = 1$.[42] Given estimates of data moments, m, to target, denote the full set of data inputs $d = (z, m)$. Our minimum-distance estimator is

$$Q(\theta) = \|g(\theta; d)\|^2, \qquad g(\theta; d) \equiv m(\theta; z) - m$$

First, we will derive the covariance of the distance metric at a known θ. To make this explicit, define this function by $h(d) \equiv g(\theta; d)$. The Jacobian of $h(d)$ with respect to the data moments, d, is

$$J_d = \begin{bmatrix} J_z & -I_P \end{bmatrix}$$

where $J_z = \partial h(d)/\partial z$ and I_P is the identity matrix of dimension P. Let the joint covariance of the estimators for the data moments be

$$\Sigma_d = \begin{bmatrix} \Sigma_{zz} & \Sigma_{zm} \\ \Sigma_{mz} & \Sigma_{mm} \end{bmatrix}$$

Then, by the delta method, the asymptotic distribution of $h(d)$ is

$$\sqrt{n}\left(g(\theta; \hat{d}) - g(\theta; d_0)\right) = \sqrt{n}\left(h(\hat{d}) - h(d_0)\right) \xrightarrow{d} \mathcal{N}(0, \underbrace{J_d \Sigma_d J_d'}_{S_g})$$

Expanding the block product gives the covariance of the distance metric, S_g,

$$\begin{aligned} S_g &= \begin{bmatrix} J_z & -I_P \end{bmatrix} \begin{bmatrix} \Sigma_{zz} & \Sigma_{zm} \\ \Sigma_{mz} & \Sigma_{mm} \end{bmatrix} \begin{bmatrix} J_z \\ -I_P \end{bmatrix} \\ &= J_z \Sigma_{zz} J_z' - J_z \Sigma_{zm} - \Sigma_{mz} J_z' + \Sigma_{mm} \end{aligned} \tag{22}$$

Second, we will propagate the uncertainty in the distance metric to uncertainty in the parameter estimates through the implicit function theorem. Define the implicit function $\theta(d)$ that solves for the parameter values that equate the model-implied moments to the provided data moments

$$g(\theta(d), d) = 0$$

In the just-identified case where $P = dim(\theta)$ and the Jacobian of $g(\theta, d)$ with respect to θ, denoted $J_\theta = \partial g(\theta, d)/\partial \theta'$, is nonsingular when evaluated at the true values of θ and d, we can

[42] In Section D.2 we omitted z from our notation for brevity, but in implementation z is the change in relative lease prices that we simulate to compute the semi-elasticity of lease shares among the August-excluded group of vehicles. The semi-elasticity is the model moment we target, the relative lease price change is a data input. To compute these standard errors, we take into account the covariance between these two moments in the data from the joint regression reported in Table A2.

totally differentiate the above equation to get

$$\frac{\partial g}{\partial \theta'} d\theta + \frac{\partial g}{\partial (z,m)'} d(z,m) = 0 \implies \frac{d\theta}{d(z,m)'} = -J_\theta^{-1} J_d$$

Therefore, by the delta method applied to the estimator $\theta(d)$,

$$\sqrt{n}(\hat{\theta} - \theta_0) = \sqrt{n}(\theta(\hat{d}) - \theta(d_0)) \xrightarrow{d} \mathcal{N}(0, \underbrace{J_\theta^{-1} J_d \Sigma_d J_d' J_\theta^{-1\prime}}_{S_\theta}) \tag{23}$$

This gives us an expression for the asymptotic covariance of the parameter estimates

$$S_\theta = J_\theta^{-1} J_d \Sigma_d J_d' J_\theta^{-1\prime} = J_\theta^{-1} S_g J_\theta^{-1\prime}$$

We compute empirical standard errors in Table 5 by numerically approximating $\hat{J}_\theta$ and $\hat{J}_z$ at the estimated parameter values along with estimating the covariance of the moments $\hat{\Sigma}_d$ in our auxiliary data. We construct the latter as follows: (1) we assume the own-price elasticity target is known with certainty and has zero covariance with the other data moments; (2) we compute the covariance between our regression estimates of the relative lease price and lease share change in the joint regression reported in Table A3 and assume zero covariance with the other data moments; and (3) we bootstrap the covariance between of the six NVES data moments by resampling with replacement the original survey responses. We assume the population distribution in the IRS SOI is known with certainty.

To construct confidence intervals for our counterfactual outcomes, we take bootstrapped draws of parameters according to the covariance matrix calculated above. We compute outcomes for each counterfactual under each draw of parameters and report 95 percent confidence sets using the 2.5th and 97.5th percentile of values in Appendix Table 7.

D.4 Sensitivity Analysis

Here we report sensitivity to assumptions on the MCPF, SCC, and CO_2 emissions.

Appendix Table A5 revisits the calculation of constrained optimal uniform subsidies under alternative assumptions. Under the global SCC, panel (e) shows a constrained optimal uniform EV subsidy of \$13,401, and a mean constrained optimal differentiated subsidy of \$17,924. Although Figure 7, panel (a), implies that the optimal policy applied to all vehicles and under the global SCC would be a tax, we find that the constrained optimal policy applied only to the 30D-eligible is a subsidy. This sign change between tax and subsidy occurs because the constrained optimal policy does not tax GVs, and encourages sufficient substitution from GVs to EVs that subsidizing EVs becomes optimal, highlighting the role of the substitution terms of our constrained optimal subsidy formulas. Appendix Table A5 also revisits results using an MCPF of 1.4, reflecting the deadweight loss of taxation. Here the constrained optimal uniform EV subsidy is \$2,567 with a domestic SCC and \$3,807 with a global SCC, or about a third of what Table 8 finds assuming an MCPF of 1.

We also compute the lifetime externalities from EVs using long-run marginal emissions of CO_2 estimates from the MidCase scenario of the National Renewal Energy Laboratory's Cambium model. We choose these estimates as an alternative to our baseline estimates since they are explicitly designed with policy evaluation and "long-term forward-looking decision-making" in mind (Gagnon et al. 2024). Additionally, they are available at a suitably disaggregated level to allow for close comparability with our baseline estimates. As with all forecasts, however, these estimates take as given a particular policy landscape; most relevant to our analysis is their assumption that the IRA credits for qualifying generation will remain in place. These long-run estimates imply carbon emissions from driving a BEV that are less than 40 percent of our baseline values. Nevertheless, due in large part to the importance of externalities from both accidents and manufacturing, this translates to a shift of only a few hundred dollars in the constrained optimal uniform subsidy under a domestic SCC. The primary welfare gains come in the form of reduced environmental damages, as the long-run estimates imply a larger reduction in emissions from replacing a GV with an EV.

Appendix Table A7 applies the decomposition from equation (12) of the constrained optimal uniform subsidies in Table 8. It decomposes these subsidies into four components—price distortions (markups and externalities); indirect substitution; profit shifting; and tax distortion. We also show the net value of US jobs gained for the planner that places weight on that outcome.[43] We find that the profit shifting motive is large, regardless of the SCC and MCPF assumptions.[44] First consider a setting with a global SCC and MCPF of 1, which Appendix Table A5 panel (e) shows has a constrained optimal uniform subsidy of \$13,393. This setting provides perhaps the largest scope for environmental benefits relative to non-environmental concerns. Appendix Table A7 shows that here the profit shifting component is \$3,609, while distortions account for the remaining \$9,784. In this scenario, reducing distortions (market power and externalities) has nearly three times the importance of profit shifting in guiding optimal policy. At the other extreme, consider a scenario with a domestic SCC and MCPF of 1.4, which in Table A5 panel (a) has a constrained optimal uniform subsidy of \$2,566. This setting gives the least scope for environmental concerns and further adds in the fiscal distortion from taxation. Here Appendix Table A7 shows that the profit shifting component of constrained optimal subsidies is \$3,321 while the externality and markup distortions account for \$3,363. Here, reducing distortions has roughly equal importance with profit shifting. However, the tax distortion component is -\$4,118, which significantly lowers the optimal scale of the policy.

[43] The tax distortion component exceeds zero only when MCPF>1, so this term does not appear in the main text equation (12) that assumes MCPF=1, but does appear in the appendix formulas (31) and (38) that allow MCPF>1. Likewise, the jobs value component is a subset of the price distortion and indirect substitution components, modeled as part of ϕ_j, though we present it separately in the table.

[44] All three counterfactual constrained optimal subsidies decrease foreign producer surplus relative to the IRA baseline. In each counterfactual, producer surplus falls most in Japan, followed by South Korea, Germany, then Sweden. These four countries have among the highest baseline EV registrations in the US. For example, the differentiated subsidy using the global SCC decreases annual Japanese producer surplus by \$1.3 billion annually.

D.5 Impacts of IRA on Investment and Other Outcomes

To learn about how additional EV manufacturing affects investment, we consulted the Clean Investment Monitor, a project from MIT and Rhodium that tracks investments in clean technology (Rhodium Group and MIT CEEPR 2025). From active investments there, two listings stand out as large recent EV assembly plant projects with sufficient information for our purposes. The Rivian facility in Normal, Illinois was recently expanded at the cost of $1.5 billion; the expansion is predicted to increase production from 50,000 to 215,000 for an increase of 165,000 vehicles/year, or a cost of $9,100 per additional vehicle/year (Channick 2025; Packowitz 2025; Rivian Automotive 2025). The Hyundai Metaplant near Savannah, Georgia consisted of $7.6 billion of investment and is projected to produce up to 500,000 vehicles/year, or a cost of $15,000 per additional vehicle/year (Hyundai Motor Group 2025). Of course, a greenfield plant may require greater investment than an expansion. Taking these two estimates as representing a potential range for investment required to produce additional EVs, the additional 272,000 US-assembled EVs we estimate are demanded in response to the IRA credits would correspond to between $2.4 and $4 billion of additional investment in assembly plants.

These back-of-the-envelope figures benefit from additional context. Assembly plants range in capacity. The Hyundai plant mentioned above has capacity twice what we estimate to be the effect of the IRA relative to the elimination of EV credits; the Tesla Fremont plant has similar capacity; and the expanded F-150 Lightning plant can handle production of up to 150,000 EVs per year (Ford Motor Company 2023; Tesla 2023; Hyundai Motor Group 2025). Of course, the increase in demand due to the IRA EV credits is divided across many different submodels, whereas each assembly plant produces one or a few submodels, so a single plant could not supply all the additional EVs demanded due to the IRA credits. Regardless, the total number of additional EVs demanded due to the EV credits is in the ballpark of the capacity of one or possibly two additional moderately large assembly plants, assuming no baseline surplus assembly capacity.

Another way of understanding the effects on the manufacturing sector is through employment in the automotive parts and final assembly sectors. The loss in domestic automotive manufacturing jobs associated with a repeal of the IRA credits is approximately 12,000.[45] The estimated cost per additional automotive manufacturing job ranges from $169,000 per job-year over pre-IRA policy to $563,000 per job-year over a scenario with no EV credits. This is 15 to 50 times larger than the $10,700 per job-year reported in Slattery (2025) for the average discretionary government subsidy awarded per promised job-year across their data. Our estimates of employment changes are relative to a baseline employment across both parts and final assembly of approximately 850,000, and so represents a fairly small fraction of the total industry employment.

[45] We calculate these effects by combining our model-implied marginal cost estimates I-O table and wage data together with assumptions grounded in prior work of the cost breakdown between parts and final assembly; see Appendix A.4 for more details.

E Analytical Model Appendix

Recall CS is consumer surplus, $PS = \sum_j q_j \mu_j$ is firm surplus, $G = \eta \sum_j q_j(\tau_j + \kappa_j)$ is government spending under an assumed MCPF, and $E = \sum_j q_j \phi_j$ is negative externalities, meaning $\phi_j > 0$ would indicate damages. As we discuss in the main text, since physical incidence is independent of economic incidence, τ_j and κ_j are perfect substitutes when there are no income-eligibility distinctions and there are infinite combinations of the two that yield the same welfare. We provide results fixing $\kappa_j = 0$ and assuming all households are income-eligible.

E.1 First-Best

To derive the total surplus-maximizing subsidies for the global planner, we take the derivative of W in equation (9) with respect to arbitrary good $j = 1$:

$$
\begin{aligned}
[\tau_1]: \quad \frac{\partial W}{\partial \tau_1} &= \frac{\partial CS}{\partial \tau_1} + \frac{\partial PS}{\partial \tau_1} - \frac{\partial G}{\partial \tau_1} - \frac{\partial E}{\partial \tau_1} = 0 \\
&= \underbrace{q_1 - \sum_j q_j \frac{\partial p_j}{\partial \tau_1}}_{\frac{\partial CS}{\partial \tau_1}} + \underbrace{\sum_j \frac{\partial q_j}{\partial \tau_1}\mu_j + \sum_j q_j \frac{\partial \mu_j}{\partial \tau_1}}_{\frac{\partial PS}{\partial \tau_1}} - \underbrace{\eta \sum_j \frac{\partial q_j}{\partial \tau_1}\tau_j - \eta q_1}_{\frac{\partial G}{\partial \tau_1}} - \underbrace{\sum_j \frac{\partial q_j}{\partial \tau_1}\phi_j}_{\frac{\partial E}{\partial \tau_1}} = 0,
\end{aligned}
\tag{24}
$$

where the first term of the second line is from an Envelope condition. Firm markups are defined by $p_j = \mu_j + c_j$, so $dp_j = d\mu_j$ given constant marginal costs. Using this and cancelling terms gives

$$
\eta \sum_j \frac{\partial q_j}{\partial \tau_1}\tau_j = \sum_j \frac{\partial q_j}{\partial \tau_1}\mu_j - \sum_j \frac{\partial q_j}{\partial \tau_1}\phi_j - (\eta - 1)q_1, \tag{25}
$$

where the last term comes from the revenue-raising cost of subsidies due to the MCPF. In particular, it represents the marginal cost of raising funds at the current subsidy level that arises from inframarginal take-up of q_1. Doing this for all goods gives a system of equations whose solution is

$$
\eta \boldsymbol{\tau}^{FB} = \underbrace{\boldsymbol{\mu}}_{\text{markup}} - \underbrace{\boldsymbol{\phi}}_{\text{negative externality}} + \underbrace{(\eta - 1)\boldsymbol{\Omega q}}_{\text{tax distortion}}, \tag{26}
$$

where $\boldsymbol{\Omega}$ is the $(J+1)\times(J+1)$ matrix of demand derivatives with representative element $[\Omega_{jr}] = \frac{\partial q_r}{\partial p_j}$. Notice that through the functional form of indirect utility in equation (3), demand derivatives with respect to subsidies are the negative of derivatives with respect to prices, $\frac{\partial q_j}{\partial \tau_r} = -\frac{\partial q_j}{\partial p_r}$. With $\eta = 1$, this becomes the standard first-best taxation result $\tau_j^{FB} = \mu_j - \phi_j$. With $\eta \neq 1$, the planner equates the total fiscal cost of the per vehicle subsidy, $\eta \tau_j^{FB}$, with the total distortion in the economy arising from unpriced externalities and transfers to inframarginal consumers.

E.2 Constrained Optimal Differentiated Subsidy

This subsection provides the derivation of a constrained optimal differentiated subsidy that only applies to a subset of goods $\mathcal{S}$. "Differentiated" means that the amount of the subsidy is allowed to differ across goods in $\mathcal{S}$. We allow the social planner to put no weight on some firms' surplus, for example a US planner that prioritizes domestic firms. We also allow the social planner to value the externalities associated with vehicle sales differently, for example a ϕ_j^{US} that uses a lower social cost of carbon or places additional weight on job creation. This nests the global planner solution when all subsidy effects are internalized.

Taking the derivative of W^{US} with respect to an arbitrary good, $j = 1$, in $\mathcal{S}$, and denoting the set of firms whose surplus does not contribute to welfare as For:

$$[\tau_1]: \quad \frac{\partial W^{US}}{\partial \tau_1} = \underbrace{q_1 - \sum_j q_j \frac{\partial p_j}{\partial \tau_1}}_{\frac{\partial CS}{\partial \tau_1}} + \underbrace{\sum_j \frac{\partial q_j}{\partial \tau_1}\mu_j + \sum_j q_j \frac{\partial \mu_j}{\partial \tau_1}}_{\frac{\partial PS}{\partial \tau_1}} \underbrace{- \eta \sum_{j\in\mathcal{S}} \frac{\partial q_j}{\partial \tau_1}\tau_j - \eta q_1}_{\frac{\partial G}{\partial \tau_1}} \underbrace{- \sum_j \frac{\partial q_j}{\partial \tau_1}\phi_j^{US}}_{\frac{\partial E}{\partial \tau_1}} \underbrace{- \sum_{j\in For} \frac{\partial \pi_j}{\partial \tau_1}}_{\frac{\partial PS^{For}}{\partial \tau_1}} = 0 \tag{27}$$

Cancelling terms as in Section E.1 gives

$$\eta \sum_{j\in\mathcal{S}} \frac{\partial q_j}{\partial \tau_1}\tau_j = \sum_j \frac{\partial q_j}{\partial \tau_1}\mu_j - \sum_j \frac{\partial q_j}{\partial \tau_1}\phi_j^{US} - \sum_{j\in For} \frac{\partial \pi_j}{\partial \tau_1} - (\eta - 1)q_1. \tag{28}$$

Notice that through the functional form of indirect utility in equation (3), demand derivatives with respect to subsidies are the negative of derivatives with respect to prices, $\frac{\partial q_j}{\partial \tau_r} = -\frac{\partial q_j}{\partial p_r}$. If we partition the sums between $\mathcal{S}$ and $\backslash\mathcal{S}$, combine terms, and substitute for price derivatives of the opposite sign, we arrive at

$$\eta \sum_{j\in\mathcal{S}} \frac{\partial q_j}{\partial p_1}\tau_j = \sum_{j\in\mathcal{S}} \frac{\partial q_j}{\partial p_1}\left(\mu_j - \phi_j^{US}\right) + \sum_{j\in\backslash\mathcal{S}} \frac{\partial q_j}{\partial p_1}\left(\mu_j - \phi_j^{US}\right) + \sum_{j\in For} \frac{\partial \pi_j}{\partial \tau_1} + (\eta - 1)q_1. \tag{29}$$

Each choice in $\mathcal{S}$ yields a first-order condition. By expressing the sums as dot products of vectors and then stacking these S equations, we get the following linear system in matrix notation where $\boldsymbol{\tau}_{\mathcal{S}}$ is an $S \times 1$ vector of optimal differentiated subsidies

$$\eta \boldsymbol{\Omega}_S \boldsymbol{\tau}_{\mathcal{S}} = \boldsymbol{\Omega}_S \left(\boldsymbol{\mu}_{\mathcal{S}} - \boldsymbol{\phi}_{\mathcal{S}}^{US}\right) + \boldsymbol{\Omega}_{\backslash S}\left(\boldsymbol{\mu}_{\backslash\mathcal{S}} - \boldsymbol{\phi}_{\backslash\mathcal{S}}^{US}\right) + \boldsymbol{m}_{For} + (\eta - 1)\boldsymbol{q}_{\mathcal{S}} \tag{30}$$

Here, $\boldsymbol{\Omega}$ is the $(J+1) \times (J+1)$ matrix of demand derivatives with representative element $[\Omega_{jr}] = \frac{\partial q_r}{\partial p_j}$, and the $S \times S$ submatrix $\boldsymbol{\Omega}_S$ contains all elements with $j \in \mathcal{S}$, $r \in \mathcal{S}$. The $S \times (J+1-S)$ submatrix $\boldsymbol{\Omega}_{\backslash\mathcal{S}}$ contains all elements with $j \in S$, $r \in \backslash\mathcal{S}$. Additionally, $\boldsymbol{m}_{For}$ is the vector of surplus impacts on foreign firms corresponding to the final term in equation (29).

Multiplying through by the inverse of $\mathbf{\Omega}_S$ gives the constrained optimal differentiated subsidy

$$\boldsymbol{\tau}_{\mathcal{S}}^{SB} = \underbrace{\frac{1}{\eta}\left(\boldsymbol{\mu}_{\mathcal{S}} - \boldsymbol{\phi}_{\mathcal{S}}^{US}\right)}_{\text{price distortion}} + \underbrace{\frac{1}{\eta}\mathbf{\Omega}_{S}^{-1}\mathbf{\Omega}_{\setminus S}\left(\boldsymbol{\mu}_{\setminus\mathcal{S}} - \boldsymbol{\phi}_{\setminus\mathcal{S}}^{US}\right)}_{\text{indirect substitution}} + \underbrace{\frac{1}{\eta}\mathbf{\Omega}_{S}^{-1}\boldsymbol{m}_{For}}_{\text{profit shifting}} + \underbrace{\frac{(\eta-1)}{\eta}\mathbf{\Omega}_{S}^{-1}\boldsymbol{q}_{\mathcal{S}}}_{\text{tax distortion}} \tag{31}$$

Intuitively, the subsidy deviates from the first-best by the amount of diversion (or "leakage") from the untargeted set of choices and to foreign firms' surplus.

To derive an expression for $\boldsymbol{m}_{For}$, we need to know $\frac{\partial \mu_j}{\partial \tau_r}$, since the change in firm surplus $\frac{\partial \pi_j}{\partial \tau_r} = \frac{\partial q_j}{\partial \tau_r}\mu_j + q_j\frac{\partial \mu_j}{\partial \tau_r}$ is a combination of consumers' demand response and firms' markup response. The full matrix of $\frac{\partial \pi_j}{\partial \tau_r}$ is the Jacobian of firm surplus with respect to subsidies. In Appendix D we show that the solution to the Nash-Bertrand pricing game is determined by the linear system

$$\boldsymbol{q} + \tilde{\mathbf{\Omega}}\boldsymbol{\mu} = \mathbf{0} \tag{32}$$

where $\tilde{\mathbf{\Omega}}$ is the Jacobian matrix of demand derivatives but modified to contain zeros whenever a firm does not own products j and r. That is, $\tilde{\mathbf{\Omega}} = \mathbf{\Omega}\odot\mathcal{H}$, where $\mathcal{H}$ is the firm product-ownership matrix ($\odot$ is the Hadamard product). We can pass the derivative with respect to $\boldsymbol{\tau}$ through to equation (32) to get,

$$\boldsymbol{J}_{\mu}(\boldsymbol{\tau}) = -\tilde{\mathbf{\Omega}}^{-1}\left(\boldsymbol{H}_{\tilde{\Omega}}(\boldsymbol{\tau})\boldsymbol{\mu} - \mathbf{\Omega}\right) \tag{33}$$

where $\boldsymbol{J}$ is the Jacobian and $\boldsymbol{H}$ is the (three-dimensional) Hessian with element $\left[H_{\tilde{\Omega}}(\boldsymbol{\tau})_{rjk}\right] = \frac{\partial^2 q_j}{\partial \tau_r \partial p_k}$. While tedious to derive for the nested logit, the Hessian of demand with respect to prices has a closed form.[46] The challenge is in getting an expression for the term in parenthesis. One can show that the (r, j)-th element of $\boldsymbol{H}_{\tilde{\Omega}}(\boldsymbol{\tau})\boldsymbol{\mu} - \mathbf{\Omega}$, with product j belonging to firm f, is given by

$$\left[\left(\sum_{k\in\mathcal{J}_{f(j)}} \frac{\partial^2 q_j}{\partial \tau_r \partial p_k}\mu_k\right) - \frac{\partial q_j}{\partial p_r}\right].$$

After being premultiplied by $-\tilde{\mathbf{\Omega}}^{-1}$, each element of the resulting matrix corresponds to $\frac{\partial \mu_j}{\partial \tau_r}$. This can be used to construct $\boldsymbol{m}_{For}$ using all $j \in For$, $r \in \mathcal{S}$.

E.3 Constrained Optimal Uniform Subsidy

This subsection provides the derivation of Proposition 1 in the main text, the constrained optimal uniform subsidy for a subset of goods $\mathcal{S}$. "Uniform" means that we restrict the value of the subsidy,

[46] Starting from equation (6), one makes extensive use of the fact that the nested logit is a complete partition of all options into separate nests. The first implication of this fact is that conditional shares take the form $s_{r|g(j)} = \frac{s_r}{s_{g(j)}}\delta_{g(r),g(j)}$, $s_{r|c(j)} = \frac{s_r}{s_{c(j)}}\delta_{c(r),c(j)}$, and $s_{r|k(j)} = \frac{s_r}{s_{k(j)}}\delta_{k(r),k(j)}$. The second implication is that unconditional nest shares simply aggregate over their member options, so $s_{g(j)} = \sum_{\ell\in\mathcal{J}} s_\ell \delta_{g(\ell),g(j)}$, $s_{c(j)} = \sum_{\ell\in\mathcal{J}} s_\ell \delta_{c(\ell),c(j)}$, and $s_{k(j)} = \sum_{\ell\in\mathcal{J}} s_\ell \delta_{k(\ell),k(j)}$. Substituting in these expressions allows one to express the Hessian purely as a function of demand derivatives, membership indicators, and the demand parameters.

τ, to be equal for all choices in $\mathcal{S}$. We proceed in a similar fashion to Section E.2. Taking the derivative of W^{US} with respect to the scalar value τ, which changes the subsidy level for all choices in $\mathcal{S}$:

$$[\tau]: \quad \frac{dW^{US}}{d\tau} = \underbrace{\sum_{j\in\mathcal{S}} q_j - \sum_j q_j \frac{dp_j}{d\tau}}_{\frac{dCS}{d\tau}} + \underbrace{\sum_j \frac{dq_j}{d\tau}\mu_j + \sum_j q_j \frac{d\mu_j}{d\tau}}_{\frac{dPS}{d\tau}}$$
$$\underbrace{-\eta \sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\tau^{SB,U} - \eta \sum_{j\in\mathcal{S}} q_j}_{\frac{dG}{d\tau}} \underbrace{- \sum_j \frac{dq_j}{d\tau}\phi_j^{US}}_{\frac{dE}{d\tau}} \underbrace{- \sum_{j\in For} \frac{d\pi_j}{d\tau}}_{\frac{dPS^{For}}{d\tau}} = 0 \tag{34}$$

Cancelling terms and rearranging gives

$$\eta \sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\tau^{SB,U} = \sum_j \frac{dq_j}{d\tau}\mu_j - \sum_j \frac{dq_j}{d\tau}\phi_j^{US} - \sum_{j\in For} \frac{d\pi_j}{d\tau} - (\eta - 1)\sum_{j\in\mathcal{S}} q_j. \tag{35}$$

Separating sums by $\mathcal{S}$ and $\backslash\mathcal{S}$ and combining terms gives

$$\eta \sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\tau^{SB,U} = \sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\left(\mu_j - \phi_j^{US}\right) + \sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau}\left(\mu_j - \phi_j^{US}\right) - \sum_{j\in For} \frac{d\pi_j}{d\tau} - (\eta - 1)\sum_{j\in\mathcal{S}} q_j. \tag{36}$$

Dividing through gives

$$\tau^{SB,U} = \frac{\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}(\mu_j - \phi_j^{US})}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}} + \frac{\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau}(\mu_j - \phi_j^{US})}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}} - \frac{\sum_{j\in For} \frac{d\pi_j}{d\tau}}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}} - \frac{(\eta-1)\sum_{j\in\mathcal{S}} q_j}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}} \tag{37}$$

Unit demand implies $\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau} = -\sum_{j\in\backslash\mathcal{S}} \frac{dq_j}{d\tau}$. This simplifies to equation (12) when $\eta = 1$, but takes the more general form:

$$\tau^{SB,U} = \underbrace{\frac{1}{\eta}\left(\bar{\mu}_{\mathcal{S}} - \bar{\phi}_{\mathcal{S}}^{US}\right)}_{\text{price distortion}} - \underbrace{\frac{1}{\eta}\left(\bar{\mu}_{\backslash\mathcal{S}} - \bar{\phi}_{\backslash\mathcal{S}}^{US}\right)}_{\text{indirect substitution}} - \underbrace{\frac{\sum_{j\in For} \frac{d\pi_j}{d\tau}}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}}}_{\text{profit shifting}} - \underbrace{\frac{(\eta-1)\sum_{j\in\mathcal{S}} q_j}{\eta\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}}}_{\text{tax distortion}} \tag{38}$$

Each of the first two terms are demand-response weighted-averages of the unpriced externality. The third term is the marginal profit shifted to foreign firms per marginal vehicle sold evaluated at the level of subsidy. The final term is the revenue-raising cost of the marginal transfer under a given MCPF. When we compute the optimal uniform subsidy for a US planner that places positive value on job creation, $\phi_j^{jobs} < 0$ (recall ϕ_j are negative externalities), we break out the contribution of the jobs component of the externality, reporting a "net jobs value" term equal to $-\frac{1}{\eta}\left(\bar{\phi}_{\mathcal{S}}^{jobs} - \bar{\phi}_{\backslash\mathcal{S}}^{jobs}\right)$.

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Table A1: **Share-Weighted Average Externalities by Vehicle Powertrain (Long-Run Grid)**

	(1)	(2)	(3)	(4)
	Electric Vehicles			
	All EVs	Battery electric vehicles	Plug-in hybrids	Gasoline vehicles
Driving CO_2 (global SCC)	3,494	2,335	9,104	13,597
Total negative externality				
Global SCC	10,539	9,343	16,332	19,327
Domestic SCC	4,816	4,496	6,368	5,689

Notes: This table presents market share-weighted average lifetime externalities across submodels within a powertrain, weighting submodels by average monthly sales in months when the submodel was available. Units are \$/vehicle.

Table A2: **Estimated Lease Moments**

Model:	(1)	(2)	(3)
Dependent variables:	Leasing share (%)	Lease price relative to purchase price ($000s)	
Variables			
Excluded Aug 2022 × July-August 2023	39.31	-5.677	-4.844
	(3.972)	(0.8275)	(1.142)
Fixed effects			
Submodel	Yes	Yes	Yes
Year-month	Yes	Yes	Yes
Fit statistics			
R^2	0.91635	0.72685	0.76565
Observations	3,988	3,165	1,903

Notes: This table presents regression results for the group of EVs which were excluded from 30D eligibility in August 2022. It compares outcomes for July-August 2023 with those from late 2022; columns 1 and 2 compare against the fourth quarter of 2022, whereas column 3 compares against December 2022 only. The regressions are weighted at the submodel level according to average registrations during the months the submodel was available, and standard errors are clustered at the model level. When calculating standard errors in the model following Appendix D.3, we estimate columns 1 and 2 jointly with stacked OLS equations, giving an estimated covariance of -1.688 along with the standard errors.

Table A3: **Estimated Purchase Price Effects**

Model:	(1)
Dependent variable:	Purchase price ($000s)
Variables	
Excluded Aug 2022 or Excluded/Reduced Apr 2023 × July-August 2023	0.3724
	(0.5065)
Fixed effects	
Submodel	Yes
Year-month	Yes
Fit statistics	
R^2	0.98994
Observations	16,047

Notes: This table presents regression results for the group of EVs which were excluded from 30D eligibility in August 2022 and in either excluded from 30D or who experienced reductions in purchase credits in April 2023. The pre-period is defined as the three months prior to the eligibility change (considered to be September 2022 and May 2023, respectively); the control group is all GVs. The regression is weighted at the submodel level according to average registrations during the months the submodel was available, and standard errors are clustered at the model level.

Table A4: **Effects of Counterfactual Policies on Market and Welfare Outcomes**

	(1)	(2)	(3)	(4)	(5)	(6)
		Repeal IRA		Modify Trade Limits		
	IRA (baseline)	Eliminate EV Credits	Return to Pre-IRA 30D with phaseout	IRA, add trade restrictions on leases	IRA, remove trade restrictions	IRA, remove income threshold
Panel (a): Market Aggregates under Counterfactual Scenario						
1. Vehicle registrations (000s/year)	10,633	10,519 [10,511, 10,527]	10,596 [10,592, 10,602]	10,613 [10,610, 10,616]	10,688 [10,683, 10,695]	10,634 [10,634, 10,634]
2. US firms (000s/year)	4,017	3,804 [3,796, 3,812]	3,738 [3,728, 3,746]	4,027 [4,024, 4,028]	3,970 [3,966, 3,972]	4,032 [4,031, 4,033]
3. Foreign firms (000s/year)	6,616	6,714 [6,709, 6,723]	6,858 [6,849, 6,871]	6,586 [6,582, 6,592]	6,718 [6,711, 6,728]	6,602 [6,601, 6,603]
4. EV registrations (000s/year)	1,184	924 [912, 937]	1,117 [1,108, 1,131]	1,134 [1,128, 1,143]	1,313 [1,304, 1,326]	1,199 [1,198, 1,200]
5. US firms (000s/year)	835	571 [561, 579]	543 [534, 550]	834 [833, 835]	812 [810, 813]	856 [855, 857]
6. Foreign firms (000s/year)	349	353 [345, 365]	574 [563, 593]	300 [293, 309]	501 [491, 516]	343 [343, 343]
7. EV market share (%)	11.1	8.8 [8.7, 8.9]	10.5 [10.5, 10.7]	10.7 [10.6, 10.8]	12.3 [12.2, 12.4]	11.3 [11.3, 11.3]
8. Lease share, within EVs (%)	29.3	9.8 [6.3, 12.1]	10.8 [7.1, 13.3]	12.9 [10.8, 14.3]	15.4 [13.1, 16.9]	26.5 [25.6, 27.0]
9. US assembly share, within EVs (%)	70.5	61.0 [60.1, 61.6]	50.6 [49.5, 51.3]	73.8 [73.1, 74.2]	61.3 [60.6, 61.8]	71.3 [71.2, 71.4]
10. Cost per additional EV ($000s/EV)	-	26.5 [25.3, 28.2]	36.5 [32.4, 45.6]	31.9 [28.4, 39.2]	13.5 [12.7, 14.1]	40.3 [35.7, 42.6]
Panel (b): Employment and Battery Production Effects Relative to IRA Baseline (000s/year)						
11. ΔUS auto manufacturing jobs	-	-12.3 [-12.9, -11.7]	-14.5 [-15.2, -13.9]	0.7 [0.5, 0.9]	-3.5 [-3.8, -3.3]	0.7 [0.7, 0.7]
12. ΔUS auto parts jobs	-	-7.8 [-8.2, -7.4]	-9.3 [-9.8, -8.9]	0.5 [0.4, 0.6]	-2.3 [-2.5, -2.2]	0.5 [0.4, 0.5]
13. ΔUS auto assembly jobs	-	-4.5 [-4.7, -4.3]	-5.2 [-5.4, -5.0]	0.2 [0.1, 0.3]	-1.2 [-1.3, -1.1]	0.2 [0.2, 0.2]
14. ΔUS-assembled EV batteries	-	-258 [-267, -249]	-289 [-298, -282]	11 [8.99, 12.4]	-34 [-37.5, -32.5]	19 [17.7, 20.1]
15. Cost per additional US job ($000s/job)	-	563 [537, 588]	169 [159, 179]	-2,160 [-3,242, -1,752]	-499 [-523, -475]	877 [753, 948]

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Table A4 (continued from previous page)	(1)	(2)	(3)	(4)	(5)	(6)
		Repeal IRA		Modify Trade Limits		
	IRA (baseline)	Eliminate EV Credits	Return to Pre-IRA 30D with phaseout	IRA, add trade restrictions on leases	IRA, remove trade restrictions	IRA, remove income threshold
Panel (c): Surplus Effects Relative to IRA Baseline ($billion/year)						
16. ΔUS consumer surplus	-	-4.84 [-4.97, -4.63]	-0.88 [-1.04, -0.59]	-1.08 [-1.20, -0.87]	2.33 [2.21, 2.55]	0.67 [0.63, 0.70]
17. ΔGlobal producer surplus	-	-1.63 [-1.67, -1.60]	-1.37 [-1.41, -1.32]	0.10 [0.07, 0.12]	-0.05 [-0.09, 0.00]	0.08 [0.07, 0.09]
18. ΔUS producer surplus	-	-2.56 [-2.65, -2.50]	-3.67 [-3.78, -3.61]	0.35 [0.27, 0.40]	-0.95 [-1.02, -0.90]	0.28 [0.26, 0.30]
19. ΔForeign producer surplus	-	0.93 [0.88, 1.00]	2.30 [2.24, 2.43]	-0.25 [-0.28, -0.19]	0.90 [0.85, 0.98]	-0.20 [-0.21, -0.19]
20. ΔCO_2 emissions (million tons/year)	-	5.74 [5.47, 5.98]	3.03 [2.80, 3.20]	0.51 [0.37, 0.60]	-2.14 [-2.34, -1.99]	-0.50 [-0.52, -0.46]
21. ΔGlobal negative externalities (global SCC)	-	1.47 [1.40, 1.53]	0.89 [0.82, 0.93]	0.11 [0.07, 0.13]	-0.55 [-0.61, -0.51]	-0.13 [-0.13, -0.11]
22. ΔUS negative externalities (domestic SCC)	-	0.25 [0.23, 0.26]	0.24 [0.23, 0.25]	0.00 [-0.01, 0.00]	-0.10 [-0.11, -0.09]	-0.02 [-0.02, -0.02]
23. ΔForeign negative externalities (foreign SCC)	-	1.22 [1.17, 1.28]	0.65 [0.60, 0.68]	0.11 [0.08, 0.13]	-0.46 [-0.50, -0.43]	-0.11 [-0.11, -0.10]
24. ΔUS government spending	-	-6.90 [-6.99, -6.86]	-2.45 [-2.49, -2.41]	-1.61 [-1.63, -1.60]	1.74 [1.69, 1.82]	0.60 [0.51, 0.66]
25. ΔGlobal surplus	-	-1.04 [-1.23, -0.72]	-0.69 [-0.88, -0.35]	0.52 [0.38, 0.76]	1.09 [0.97, 1.31]	0.28 [0.25, 0.32]
26. ΔUS total surplus (global SCC)	-	-1.97 [-2.11, -1.73]	-2.99 [-3.12, -2.77]	0.77 [0.66, 0.95]	0.19 [0.12, 0.33]	0.48 [0.45, 0.52]
27. ΔUS total surplus (domestic SCC)	-	-0.74 [-0.85, -0.53]	-2.35 [-2.44, -2.17]	0.88 [0.79, 1.03]	-0.27 [-0.32, -0.17]	0.37 [0.34, 0.42]
28. ΔForeign total surplus (foreign SCC)	-	-0.30 [-0.39, -0.18]	1.66 [1.56, 1.82]	-0.36 [-0.41, -0.27]	1.36 [1.28, 1.48]	-0.09 [-0.10, -0.09]
Panel (d): Welfare Cost per Ton of CO_2 Abated						
29. Global cost/ton CO_2 abated ($/ton)	-	59.8 [32.5, 109]	13.8 [-35.7, 119]	1,269 [869, 2,258]	-268 [-324, -229]	-318 [-457, -248]
30. US cost/ton CO_2 abated ($/ton)	-	-101 [-119, -65.8]	-747 [-772, -722]	1,759 [1,330, 2,761]	152 [101, 184]	-719 [-870, -642]
Panel (e): MVPF of Higher-Spending versus Lower-Spending Scenario						
31. Global MVPF	-	1.15 [1.10, 1.18]	1.28 [1.14, 1.36]	0.68 [0.53, 0.76]	1.63 [1.56, 1.72]	1.46 [1.39, 1.64]
32. US MVPF (global SCC)	-	1.28 [1.25, 1.31]	2.22 [2.14, 2.26]	0.52 [0.41, 0.59]	1.11 [1.07, 1.18]	1.79 [1.70, 2.01]
33. US MVPF (domestic SCC)	-	1.11 [1.08, 1.12]	1.96 [1.90, 1.99]	0.45 [0.37, 0.50]	0.85 [0.81, 0.91]	1.61 [1.53, 1.82]

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Table A4 (continued from previous page)	(1)	(2)	(3)	(4)	(5)	(6)
		Repeal IRA		Modify Trade Limits		
	IRA (baseline)	Eliminate EV Credits	Return to Pre-IRA 30D with phaseout	IRA, add trade restrictions on leases	IRA, remove trade restrictions	IRA, remove income threshold
Panel (f): Allocation of EV Credits						
34. Share of EVs with credits (%)	79.7	0.00	65.9	66.8	87.8	86.8
		[0.00, 0.00]	[65.2, 67.0]	[66.5, 67.2]	[87.4, 88.5]	[86.7, 86.8]
35. Among HHs >$300k (%)	44.0	0.00	64.8	23.0	41.5	78.7
		[0.00, 0.00]	[64.2, 65.7]	[20.8, 26.7]	[39.9, 43.9]	[77.5, 79.3]

Notes: This table reproduces Table 7 with bootstrapped 95% confidence intervals calculated as described in Section D.3. We take 499 draws of the parameters according to the estimated covariance matrix and report the 2.5th and 97.5th percentiles of each outcome.

Table A5: **Counterfactual Simulation Results: Sensitivity Analysis**

		(1) IRA	(2) US-optimal uniform EV subsidy with 30D restrictions	(3) US-optimal differentiated EV subsidy with 30D restrictions
	Panel (a): Marginal Cost of Public Funds = 1.4, Social Cost of Carbon = $28			
1.	Mean EV subsidy	$7,180	$2,567	$3,807
2.	ΔGlobal negative externalities	-0.25	-0.04	-0.38
3.	ΔGlobal surplus	-2.95	-0.32	-0.39
4.	ΔUS total surplus (global SCC)	-2.02	0.21	0.39
5.	Cost per additional EV ($000s/EV)	37.1	31.5	38.0
6.	US MVPF (global SCC)	0.79	1.09	1.11
	Panel (b): Marginal Cost of Public Funds = 1.4, Social Cost of Carbon = $241			
1.	Mean EV subsidy	$7,180	$4,725	$7,003
2.	ΔGlobal negative externalities	-1.47	-0.74	-2.00
3.	ΔGlobal surplus	-1.72	-0.31	-0.16
4.	ΔUS total surplus (global SCC)	-0.80	0.69	1.20
5.	Cost per additional EV ($000s/EV)	37.1	33.7	41.8
6.	US MVPF (global SCC)	0.92	1.14	1.15
	Panel (c): Social Cost of Carbon = $100			
1.	Mean EV subsidy	$7,180	$10,847	$13,864
2.	ΔGlobal negative externalities	-0.66	-0.87	-2.17
3.	ΔGlobal surplus	0.23	0.21	0.64
4.	ΔUS total surplus (global SCC)	1.16	2.70	3.73
5.	Cost per additional EV ($000s/EV)	26.5	28.2	33.0
6.	US MVPF (global SCC)	1.17	1.22	1.22
	Panel (d): Social Cost of Carbon = $200			
1.	Mean EV subsidy	$7,180	$12,641	$16,715
2.	ΔGlobal negative externalities	-1.23	-2.18	-4.69
3.	ΔGlobal surplus	0.80	0.72	1.58
4.	ΔUS total surplus (global SCC)	1.73	3.69	5.33
5.	Cost per additional EV ($000s/EV)	26.5	29.4	35.2
6.	US MVPF (global SCC)	1.25	1.23	1.23
	Panel (e): Social Cost of Carbon = $241			
1.	Mean EV subsidy	$7,180	$13,401	$17,924
2.	ΔGlobal negative externalities	-1.47	-2.87	-6.04
3.	ΔGlobal surplus	1.04	0.98	2.08
4.	ΔUS total surplus (global SCC)	1.97	4.16	6.13
5.	Cost per additional EV ($000s/EV)	26.5	29.8	36.1
6.	US MVPF (global SCC)	1.28	1.24	1.23

Notes: This table presents sensitivity analysis for counterfactual simulation results presented in Table 7. All results are relative to the scenario with no EV credits. For each scenario, in column 2 we simulate the uniform EV subsidy subject to Section 30D trade restrictions that maximizes US total surplus and, in column 3, the choice-specific differentiated EV subsidy that maximizes US total surplus. The defaults are an MCPF of 1 and an SCC of $241. Mean and standard deviation of subsidies are computed only on EVs which are eligible to receive subsidies among income-eligible households as implied by the model. The set of EVs eligible to receive subsidies in all scenarios are those vehicles already eligible under 30D in the IRA. Uniform subsidy scenarios do not impose any household income restrictions whereas the IRA does. "US total surplus" equals "[global] total surplus" minus foreign automakers' producer surplus.

Table A6: **Counterfactual Simulation Results: Model Robustness**

		(1) Main specification	(2) Homogeneous demand	(3) Foreign/ domestic nest	(4) Elasticity of -4	(5) Nocke-Schutz restriction	(6) Non-Tesla EVs priced at cost
	Panel (a): Market Aggregates under Counterfactual Scenario						
1.	ΔVehicle registrations (000s/year)	114	168	93.8	92.0	170	142
2.	ΔEV registrations (000s/year)	260	307	209	205	312	318
3.	ΔEV market share (pp)	2.4	2.76	1.88	1.85	2.80	2.78
4.	ΔLease share, within EVs (pp)	19.5	17.1	19.0	19.1	17.1	26.2
5.	ΔUS assembly share, within EVs (pp)	9.49	10.4	7.53	7.60	11.0	11.1
	Panel (b): Surplus Effects Relative to No EV Subsidy Baseline ($billion/year)						
6.	ΔUS consumer surplus	4.84	5.10	5.17	5.16	5.17	6.05
7.	ΔGlobal producer surplus	1.63	2.11	1.69	1.71	1.84	0.26
8.	ΔUS producer surplus	2.56	2.93	2.70	2.73	2.66	1.29
9.	ΔForeign producer surplus	-0.93	-0.82	-1.01	-1.02	-0.81	-1.03
10.	ΔGlobal neg. externalities (global SCC)	-1.47	-1.54	-1.20	-1.17	-1.58	-1.43
11.	ΔUS neg. externalities (dom. SCC)	-0.25	-0.21	-0.21	-0.20	-0.21	-0.17
12.	ΔForeign neg. externalities (for. SCC)	-1.22	-1.33	-0.99	-0.97	-1.36	-1.25
13.	ΔUS government spending	6.90	7.38	6.85	6.85	7.38	8.91
14.	ΔGlobal surplus	1.04	1.37	1.22	1.19	1.21	-1.17
15.	ΔUS total surplus (global SCC)	1.97	2.19	2.23	2.21	2.03	-0.14
16.	ΔUS total surplus (dom. SCC)	0.74	0.86	1.23	1.24	0.67	-1.39
17.	ΔForeign total surplus (for. SCC)	0.30	0.51	-0.02	-0.05	0.55	0.22
	Panel (c): Impacts on CO_2 Relative to No EV Subsidy Baseline						
18.	ΔCO_2 emissions (million tons/year)	-5.74	-6.25	-4.66	-4.56	-6.39	-5.88
	Panel (d): Employment and Battery Production Effects Relative to No EV Subsidy Baseline (000s/year)						
19.	ΔUS auto manufacturing jobs	12.3	15.3	8.87	8.84	16.3	15.4
20.	ΔUS auto parts jobs	7.8	9.80	5.62	5.62	10.4	9.70
21.	ΔUS auto assembly jobs	4.5	5.53	3.25	3.23	5.88	5.67
	Panel (e): MVPF versus No EV Subsidy Baseline						
22.	Global MVPF	1.15	1.19	1.18	1.17	1.16	0.87
23.	US MVPF (global SCC)	1.28	1.30	1.33	1.32	1.28	0.98
24.	US MVPF (domestic SCC)	1.11	1.12	1.18	1.18	1.09	0.84
25.	Cost per additional EV ($000s/EV)	26.5	24.0	32.8	33.4	23.6	28.0
26.	Cost per additional US job ($000s/job)	563	481	772	775	453	580
27.	US-optimal uniform EV subsidy with 30D restrictions	$9,606	$8,443	$12,855	$12,942	$7,759	$3,132

Notes: This table presents simulation results comparing outcomes under the IRA against a counterfactual with no EV subsidies. Column 1 is the main specification also reported in Table 7. Column 2 reports a specification that restricts all coefficients interacted with income and does not account for income-eligibility. Column 3 modifies the nested logit assumption by replacing the vehicle class nest in the second level of the tree in Figure A15 with the US- or foreign-firm classification. Column 4 targets an alternative, more inelastic own-price model-level elasticity. Column 5 modifies the supply side assumptions under the same homogeneous demand model in column 2 as discussed in Section 6. Column 6 restricts all firms except Tesla to pricing their EVs at marginal cost.

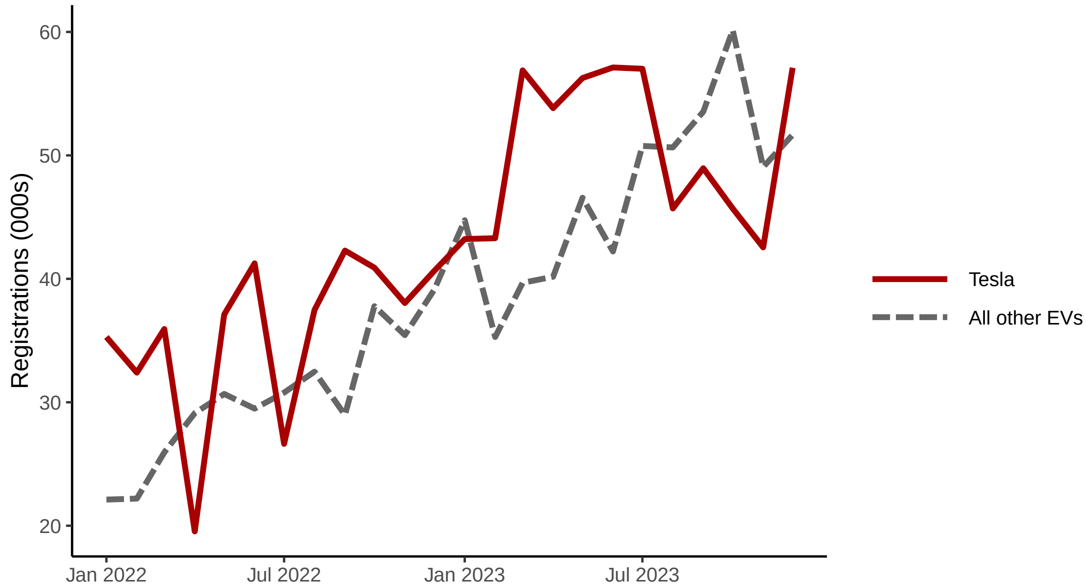
Table A7: **Decomposition of Constrained Optimal Uniform Subsidies**

	MCPF = 1.0, SCC = \$28, Job = \$0	MCPF = 1.4, SCC = \$28, Job = \$0	MCPF = 1.0, SCC = \$241, Job = \$0	MCPF = 1.4, SCC = \$241, Job = \$0	MCPF = 1.0, SCC = \$28, Job = \$10.7k	MCPF = 1.0, SCC = \$241, Job = \$10.7k
Price distortion	\$5,793	\$3,928	-\$2,880	-\$2,304	-\$5,821	-\$2,853
Indirect substitution	-\$128	-\$565	\$12,664	\$8,154	-\$85	\$12,728
Net jobs value	–	–	–	–	\$485	\$485
Externality Subtotal	*\$5,664*	*\$3,363*	*\$9,784*	*\$5,850*	*\$6,221*	*\$10,361*
Profit shifting	\$3,933	\$3,321	\$3,609	\$3,155	\$3,889	\$3,569
Tax distortion	–	-\$4,118	–	-\$4,279	–	–
Uniform subsidy	\$9,597	\$2,566	\$13,393	\$4,725	\$10,111	\$13,929

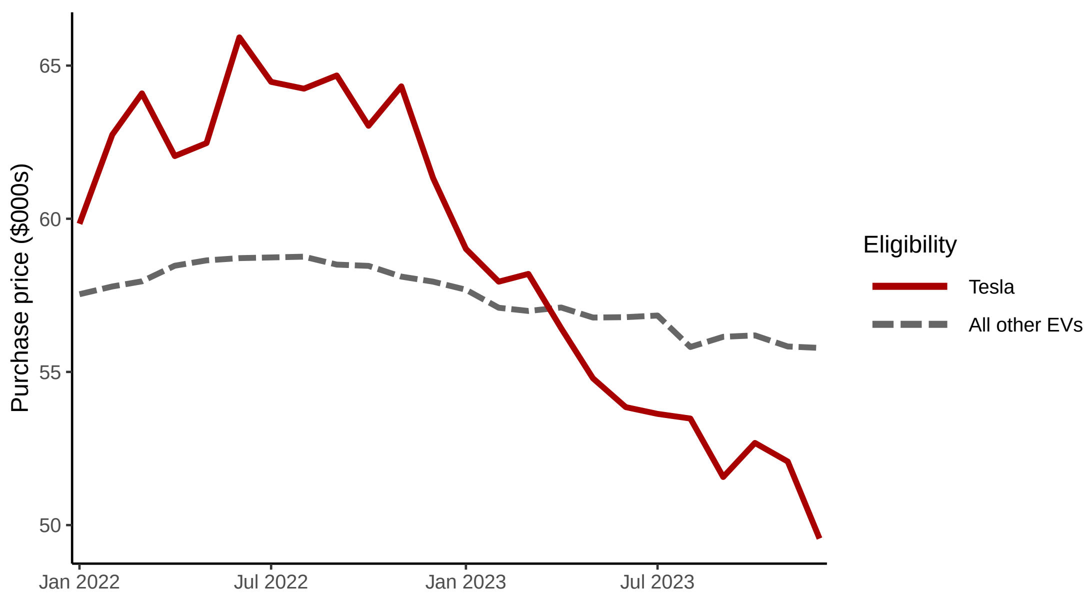
Notes: This table presents the decomposition of constrained optimal uniform subsidies for a US social planner under given values of the marginal cost of public funds and social cost of carbon. Each component corresponds to the respective term in proposition 1, using equation (38) in the appendix for the more general case of an MCPF greater than one. The value of jobs is treated as an externality in the formula but reported separately as the value placed on net additional US manufacturing jobs. The combined externality and markup components sum to the subtotal displayed in row 4. Columns 1 and 5 correspond to the uniform subsidies calculated in Table 8. Columns 2-4 correspond to uniform subsidies calculated in Table A5 under, respectively, panels (a), (e), and (b). The decomposition was calculated by numerically approximating the derivatives in equation (38) at the subsidy value. Note how the price distortion terms (row 1) relates to the distribution of price distortions in Figure 7, panels (a) and (b): under a global social cost of carbon, the price distortion alone implies a tax, whereas under a domestic social cost of carbon, the price distortion alone implies a subsidy.

Figure A1: **Monthly Registrations and Prices of Teslas and Other EVs**

(a) **Registrations**



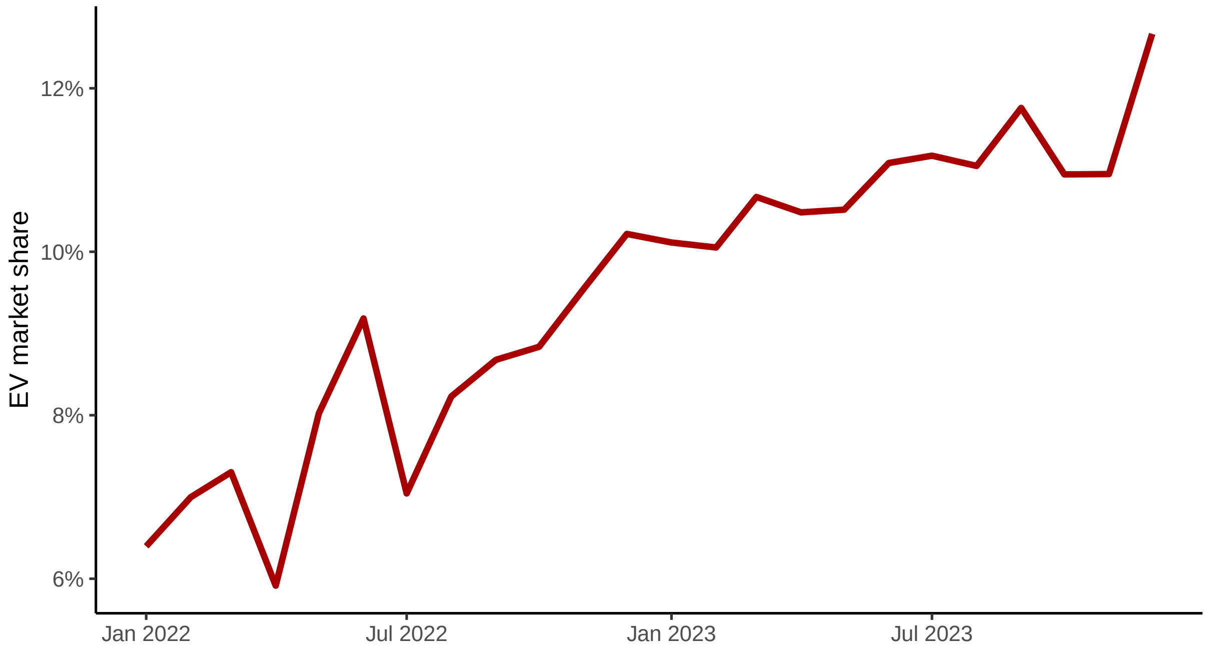
(b) **Average Purchase Prices**



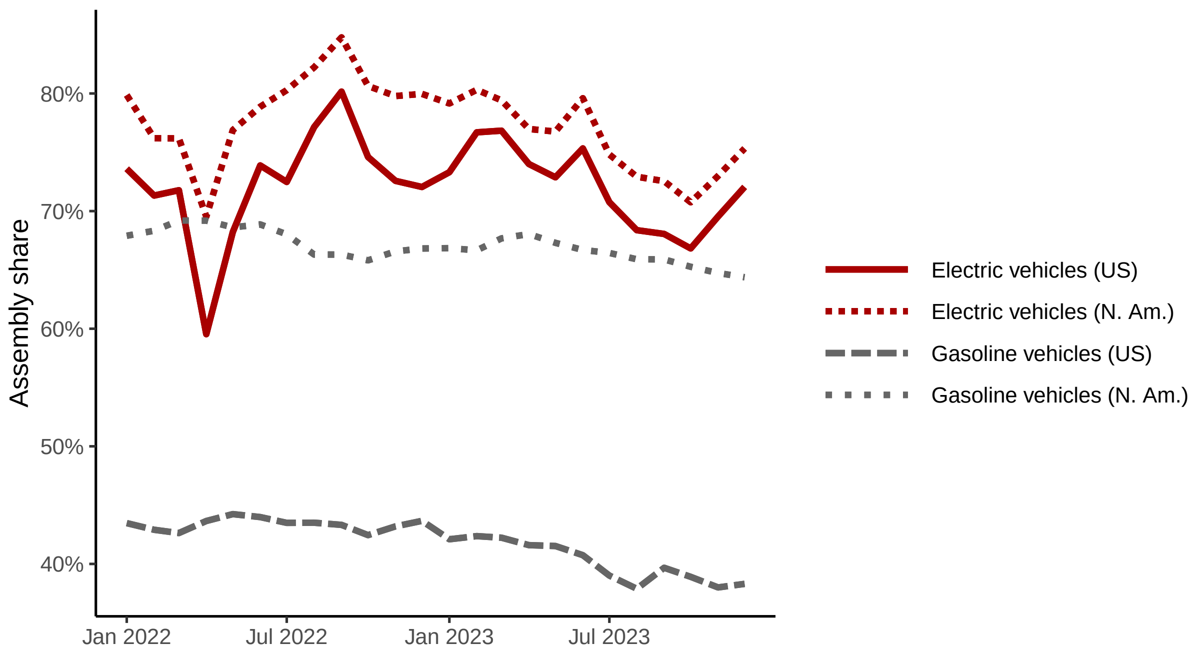
Notes: Panel (a) presents monthly registrations of Teslas and other EVs. Panel (b) presents price indexes constructed by computing the January 2023 weighted averages (weighting models by average monthly sales in months when the model was available) for Tesla and non-Tesla EVs, and then recursively adding the sales-weighted average changes for all models available in each previous or subsequent month.

Figure A2: **Aggregate Electric Vehicle Market Trends**

(a) **Share of New Vehicle Registrations that Are Electric Vehicles**



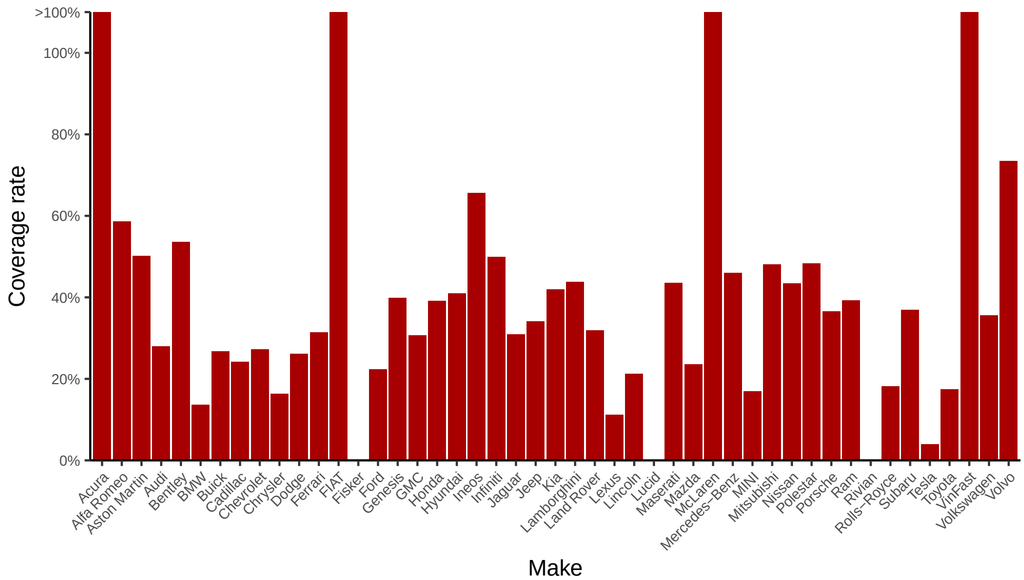
(b) **Share of New Electric Vehicle Registrations that Are Assembled in the US**



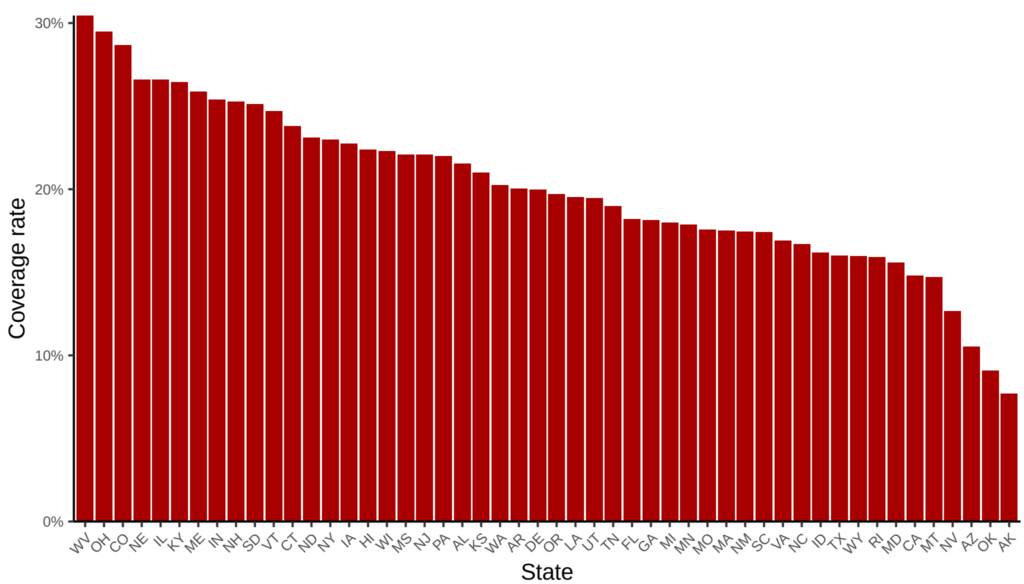
Notes: Panel (a) presents the share of new vehicle registrations that are EVs. Panel (b) presents the share of new vehicles registered that are assembled in the United States or in North America broadly.

Figure A3: **Cox Data Coverage Rate**

(a) **Cox Data Coverage Rate by Make**

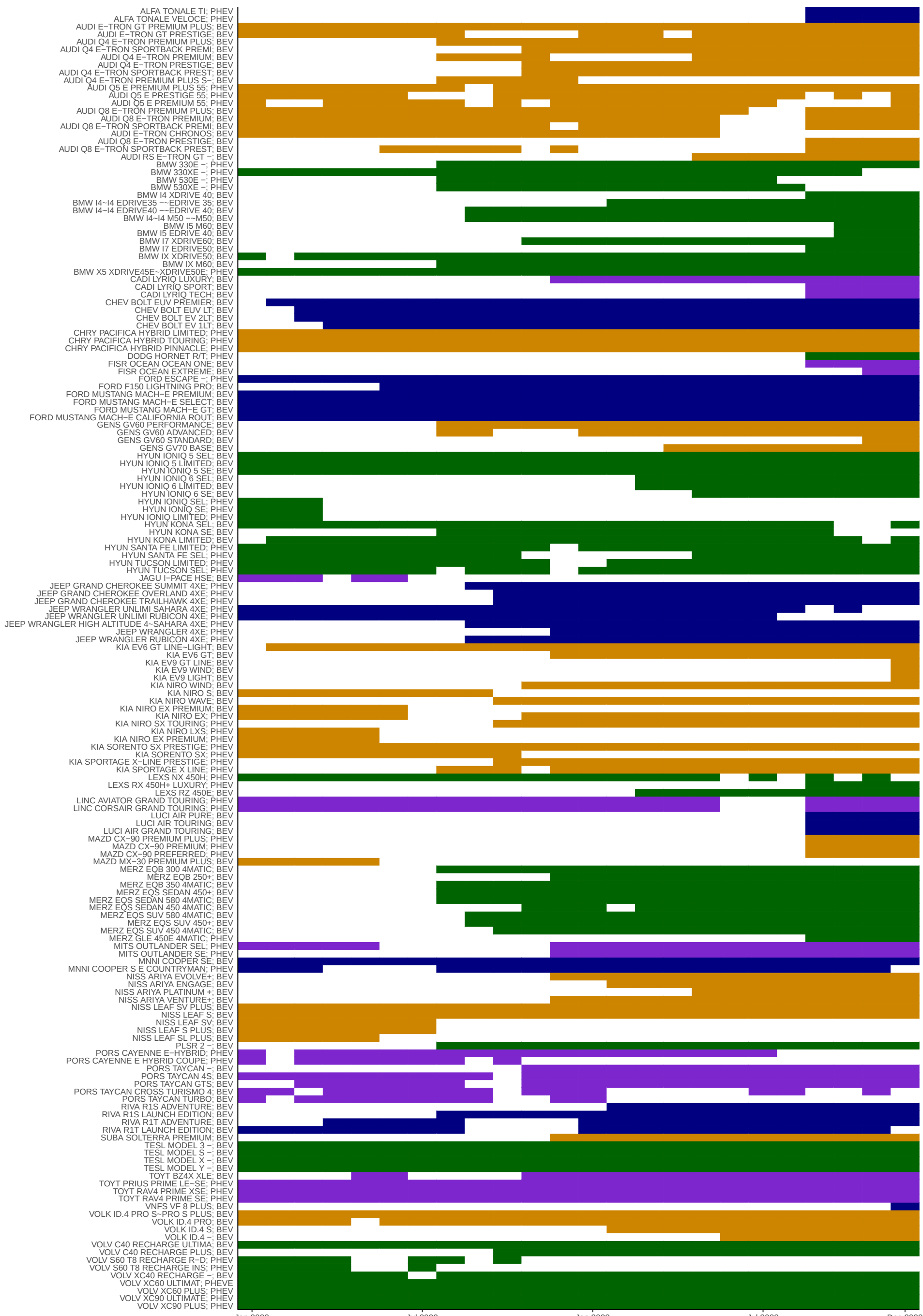


(b) **Cox Data Coverage Rate by State**



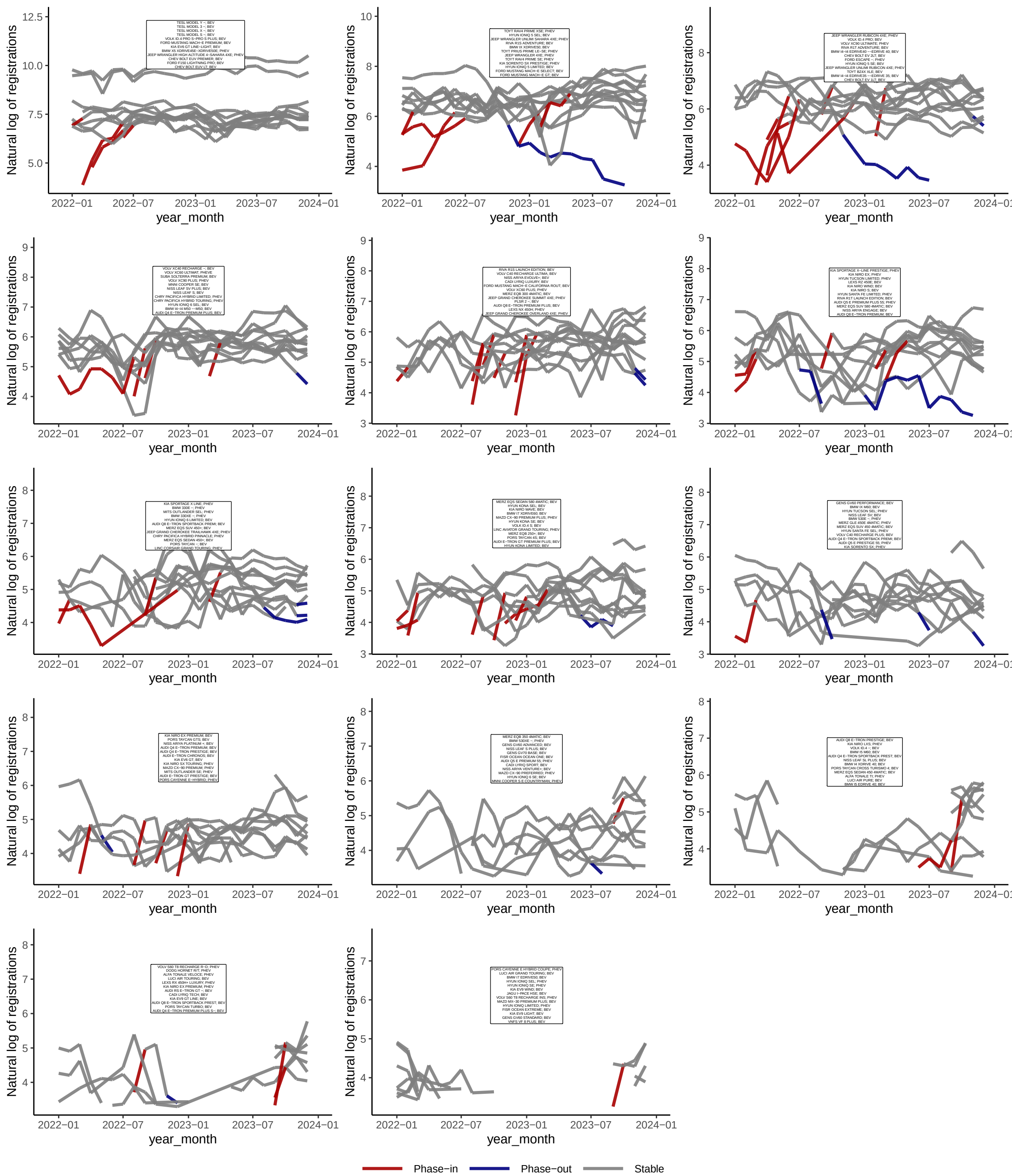
Notes: Panel (a) shows the ratio of new vehicle transactions in the Cox dealership data to nationwide new vehicle registrations in the Experian data, for each make. Panel (b) shows the ratio of new vehicle transactions in the Cox dealership data to state-level registrations from 2023.

Figure A4: **Availability by Month for Each Electric Vehicle Submodel**



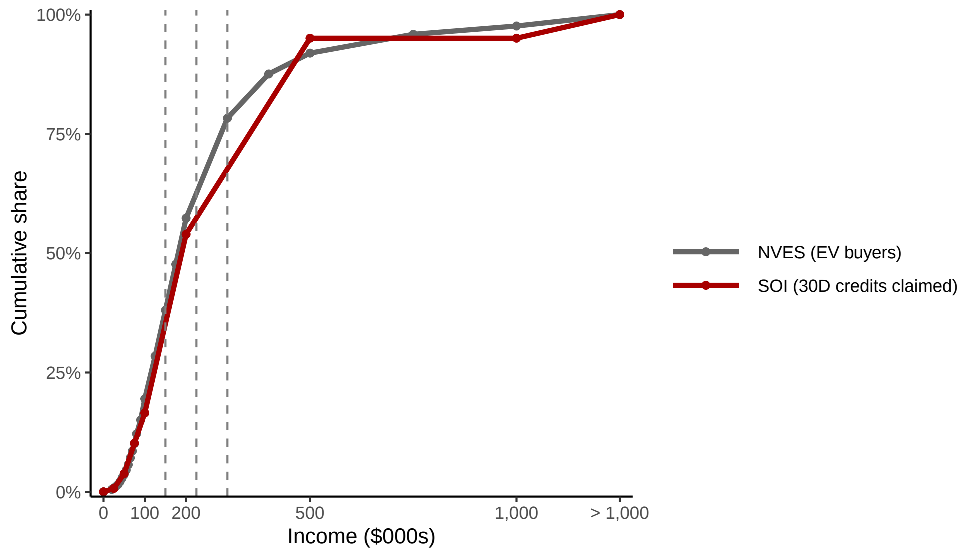
Notes: This figure has one row for each EV submodel in the data, and one column for each month of the sample. A cell is shaded if the submodel has more than 25 new registrations in that month.

Figure A5: **Phase-In and Phase-Out Periods by Submodel**



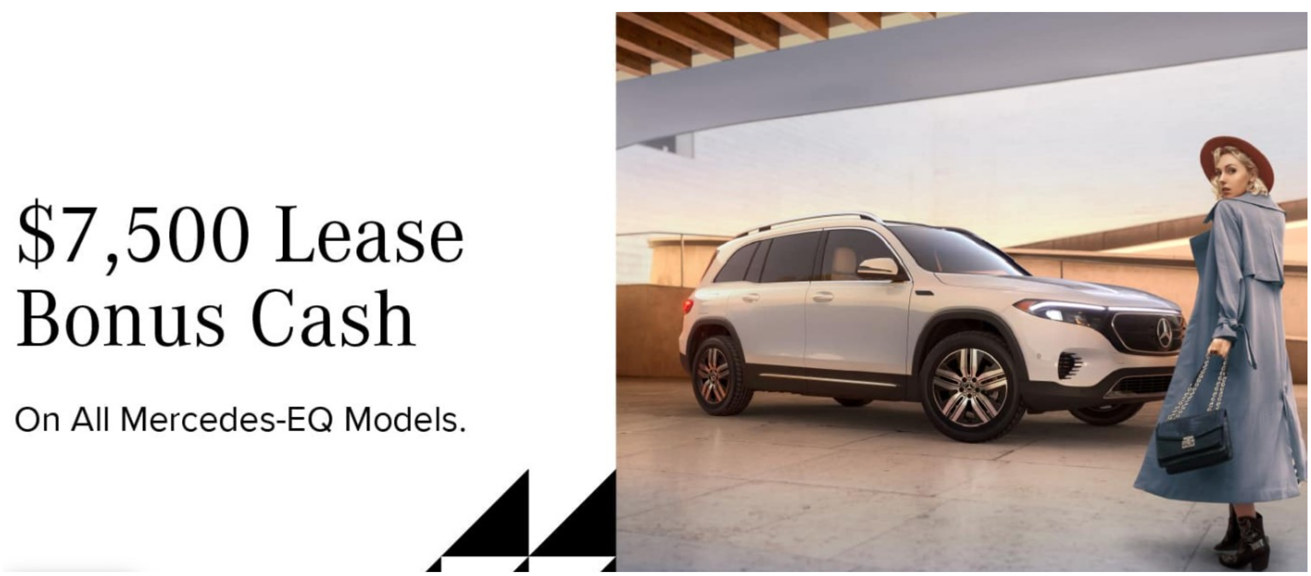
Notes: This figure presents registrations by submodel, with one line for each EV submodel in our data; we arrange them into subplots to aid in seeing the dynamics of each series. Each panel contains a group of submodels, arranged by group in decreasing order of total registrations. Red and blue lines represent phase-in and phase-out periods at the beginning and end of a submodel's life. To define these periods, we construct $\bar{q}_j$ as submodel j's sample average monthly registrations in months with non-zero registrations. Phase-in periods are consecutive months beginning with zero registrations and ending when registrations first exceed $\bar{q}_j/2$. Analogously, phase-out periods are consecutive months ending when registrations reach zero and beginning when registrations last exceed $\bar{q}_j/2$.

Figure A6: **Income Distributions for EV Buyers in 2022/2023 and 30D Tax Credit Claimants in 2021**



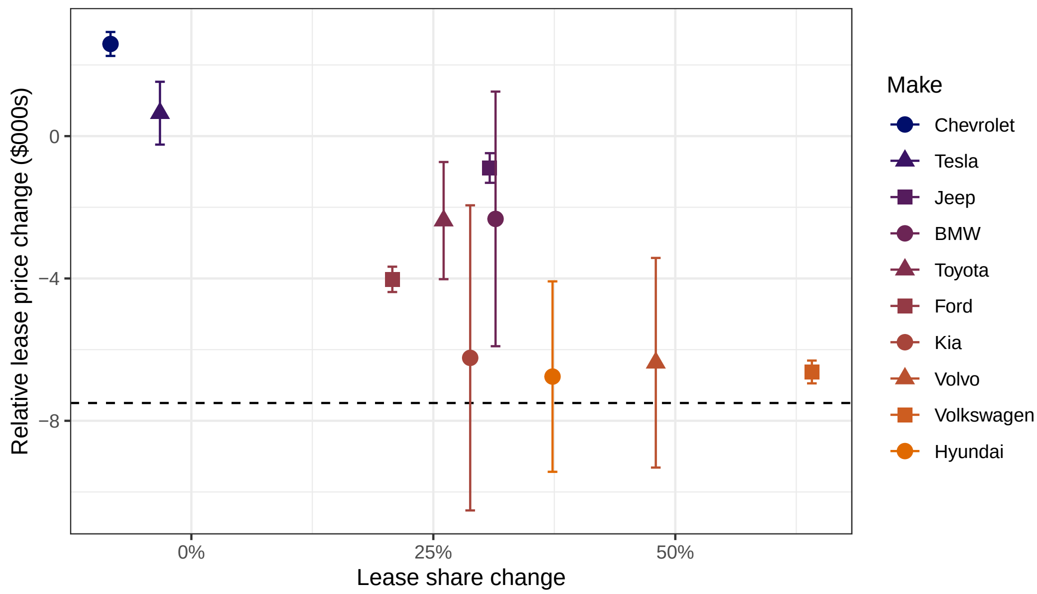
Notes: The red line shows the cumulative distribution function (CDF) of Adjusted Gross Income (AGI) for taxpayers claiming the Section 30D credit for tax year 2021, using data from the IRS Statistics of Income (2023). The grey line shows the CDF of self-reported household income for people who bought new EVs in 2022 and 2023, using data from the National Vehicle Experience Survey. The IRA requires that to be eligible to claim the credit in 2023 and after, individual buyers must have AGI below $300,000 for married couples filing jointly, $225,000 for household heads, or $150,000 for all other taxpayers. The vertical lines reflect those income thresholds.

Figure A7: **Example of Promotional Material Advertising $7,500 Lease Bonus**



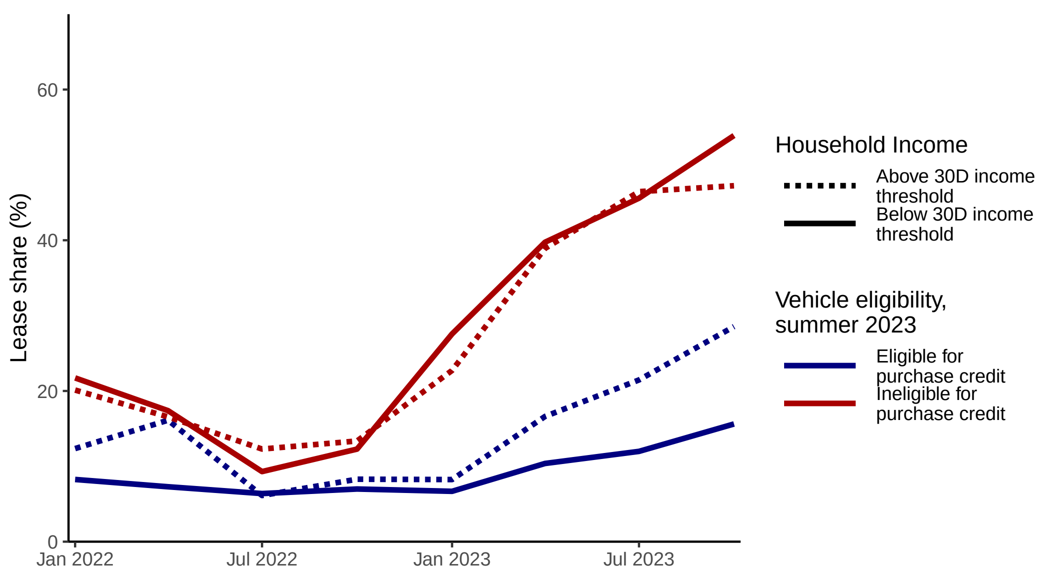
Notes: Representative screenshot showing $7,500 promotion on EV leases. Observed on the Mercedes-Benz website, August 2023.

Figure A8: **Changes in Relative Lease Prices and Lease Shares from October-December 2022 to July-August 2023 by Make**



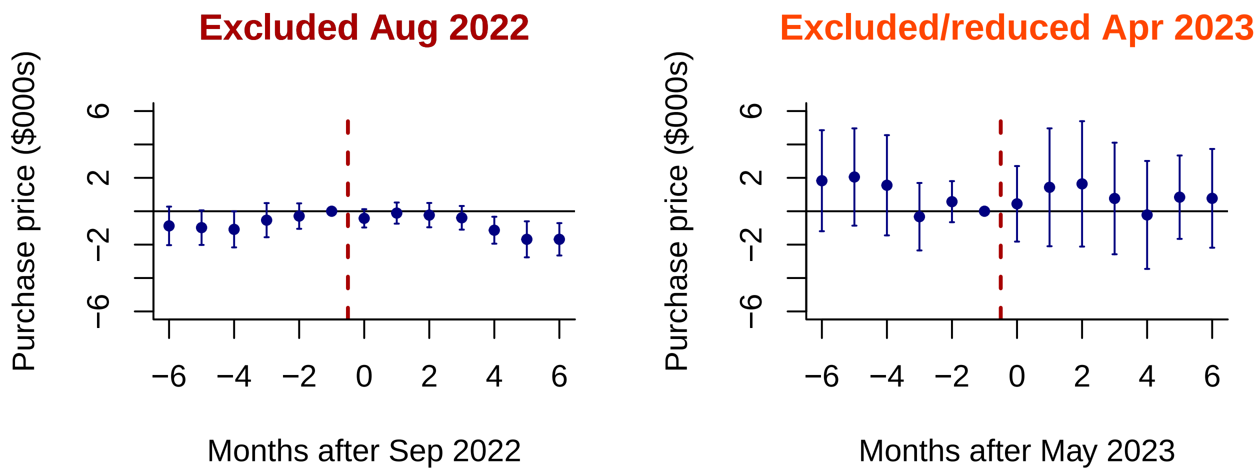
Notes: This figure presents the differences (from July-August 2023 vs. October-December 2022) in relative lease prices and lease shares, for the top-10 selling EV brands.

Figure A9: **Lease Share Trends Among Income Eligibility Groups**



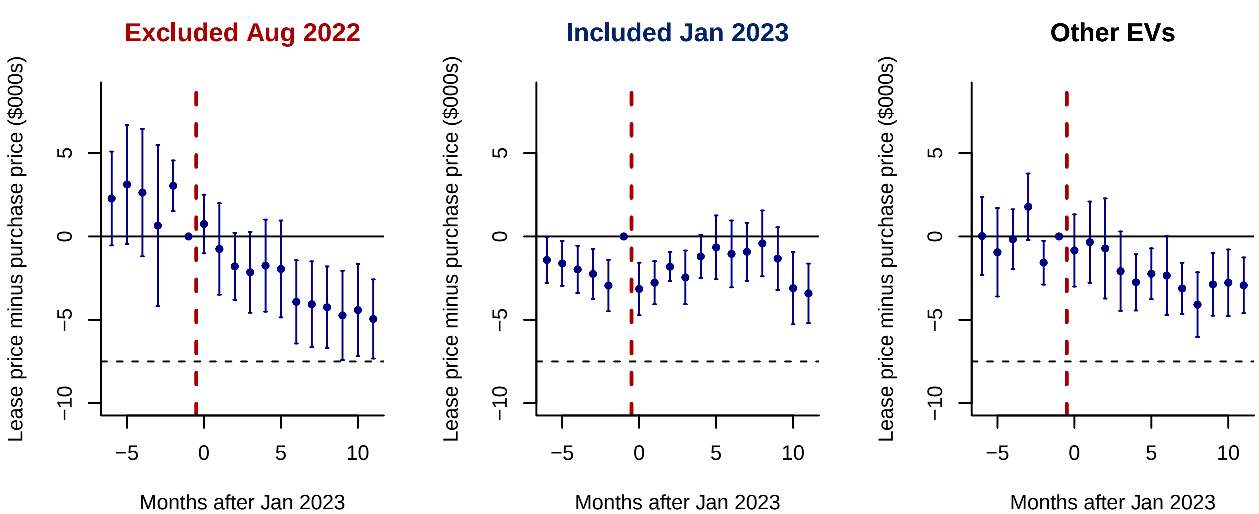
Notes: This figure presents quarterly lease shares among EVs in the NVES survey, separately shown for households above and below the income threshold for 30D credits and for vehicles which were eligible and ineligible for 30D credits in July and August 2023. This aggregation is slightly different than that shown in Figure 5, as we here group EVs only on their purchase credit eligibility as of summer 2023. Households' responses are aggregated using the survey weights and household-level eligibility is determined using self-reported household income and marital status.

Figure A10: **Purchase Price Event Study with Reweighted Controls**



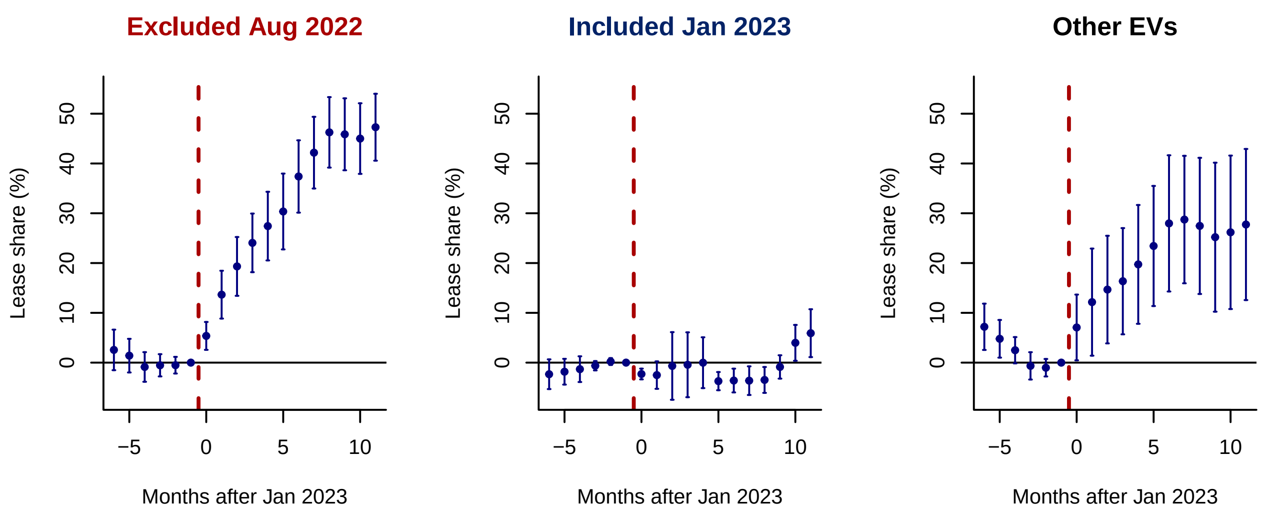
Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1. This parallels Figure A13, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

Figure A11: **Lease Price Event Study with Reweighted Controls**



Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1. This parallels Figure 4, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

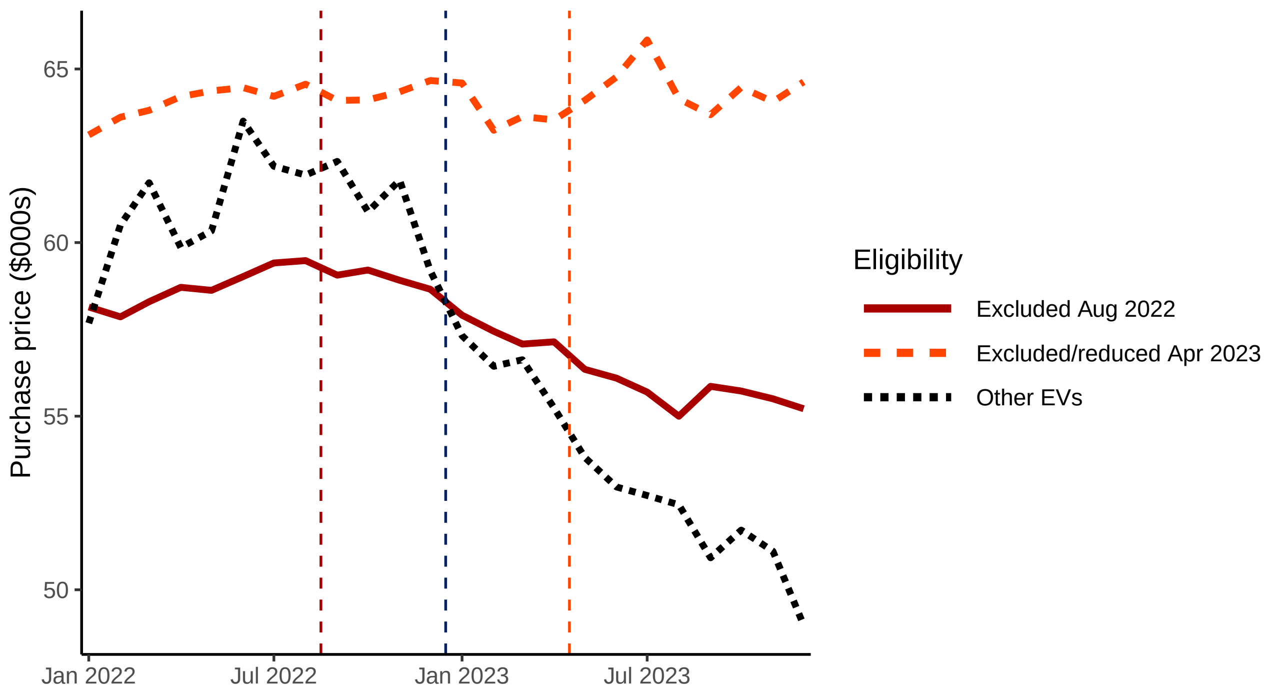
Figure A12: **Lease Share Event Study with Reweighted Controls**



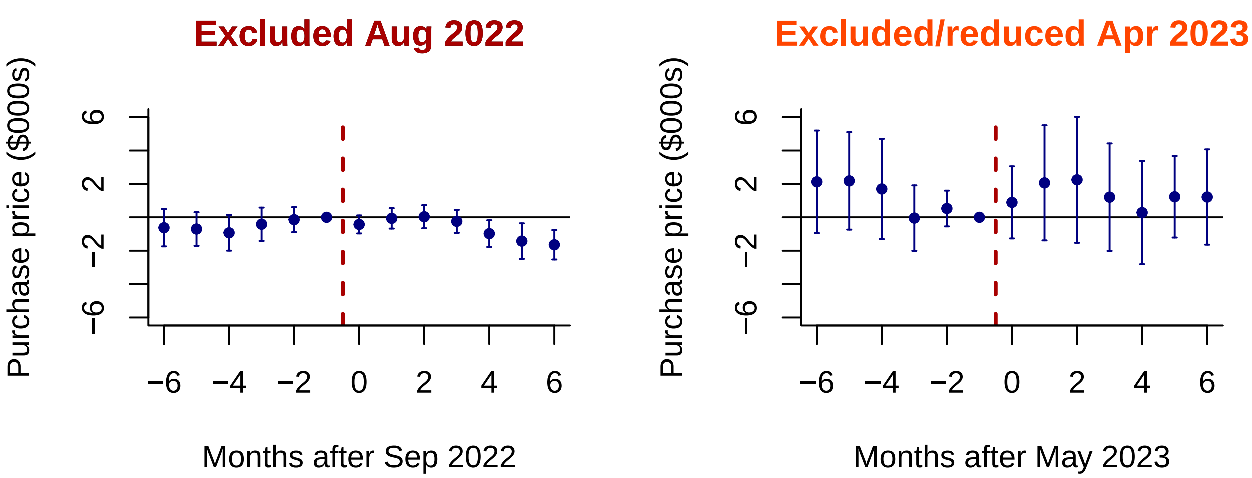
Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1. This parallels Figure 5, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

Figure A13: **Purchase Price Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



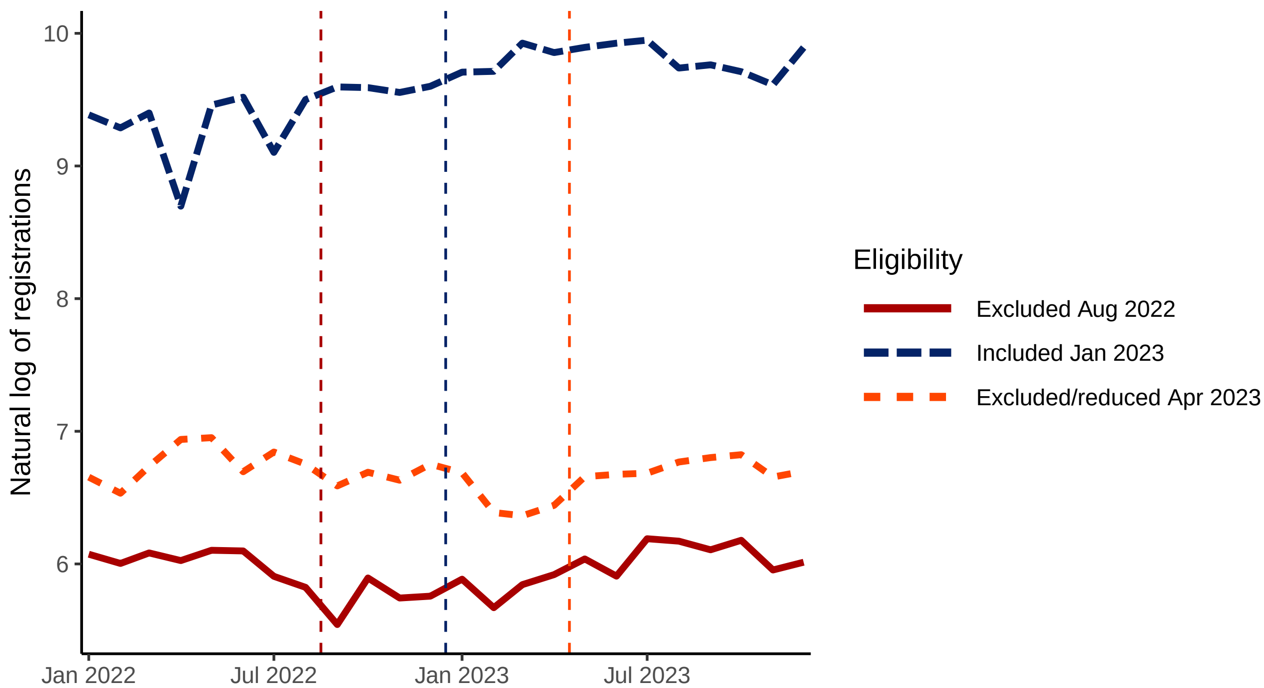
(b) **Event Study Estimates**



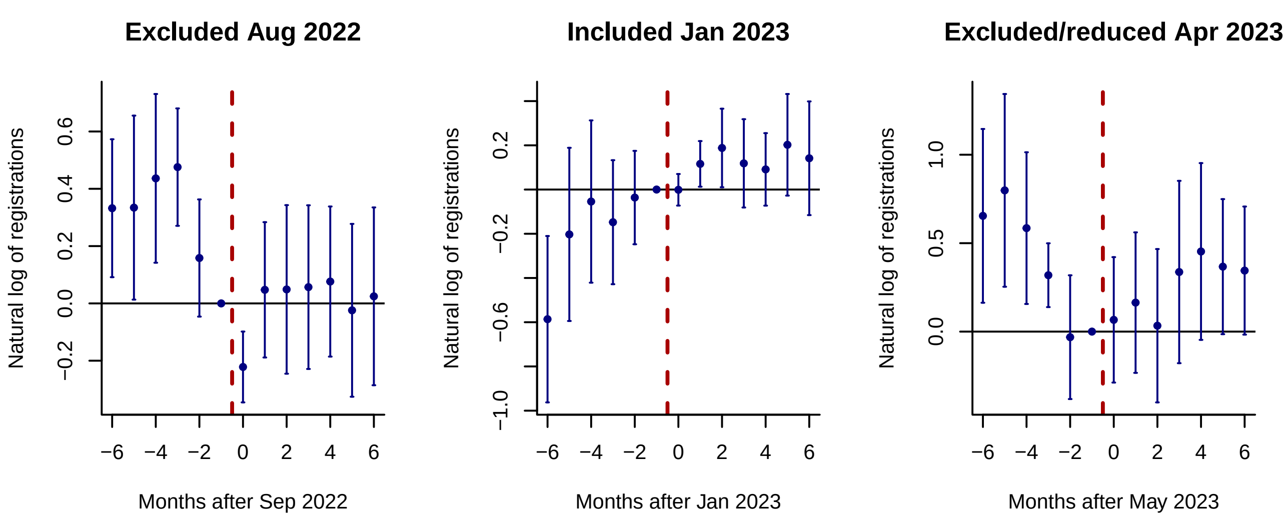
Notes: Panel (a) presents purchase price indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1; the Other EVs group includes all EVs not part of either the Excluded August 2023 or the Excluded/reduced April 2023 groups. In both panels, we weight submodels by average monthly sales in months when the submodel was available.

Figure A14: **Registration Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



(b) **Event Study Estimates**



Notes: Panel (a) presents ln(registrations) indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (2). Eligibility groups are described in Figure 1. In both panels, we weight submodels by average monthly sales in months when the submodel was available.

Figure A15: Nested Logit Structure

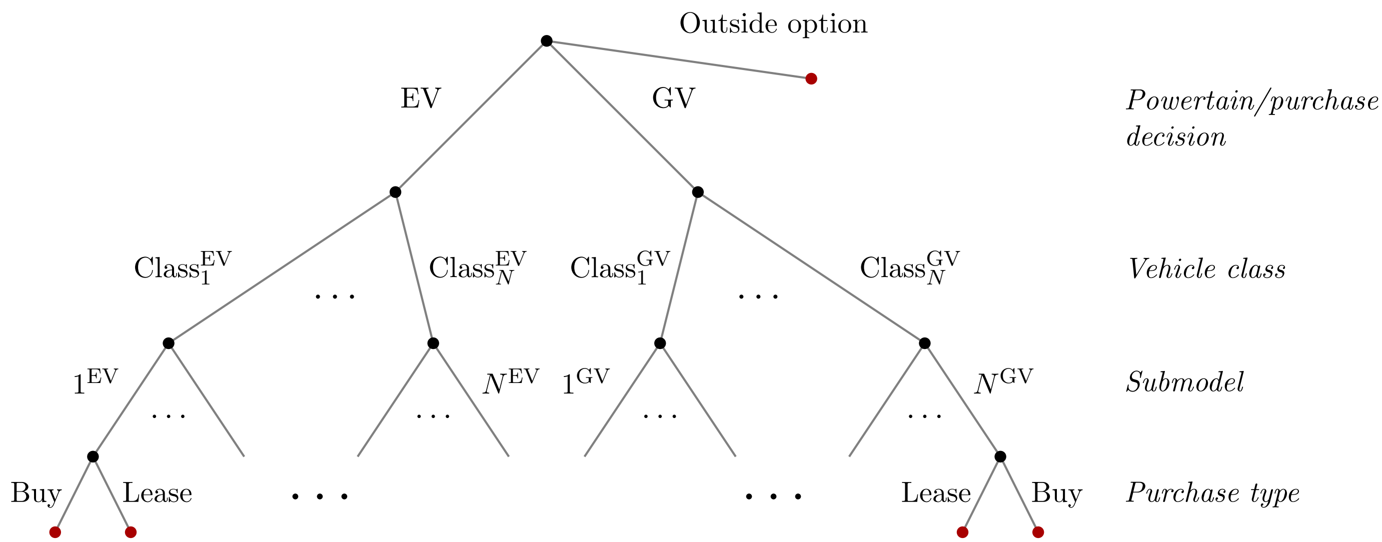
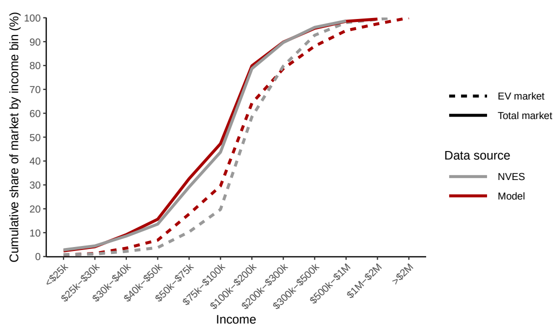
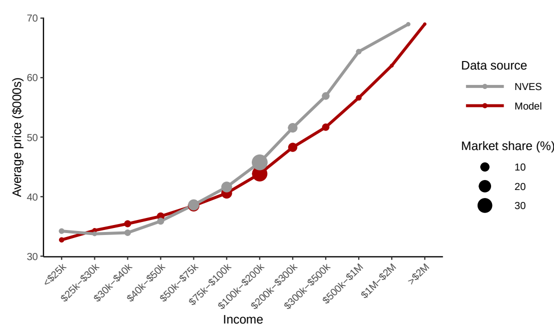


Figure A16: **Model Fit along Income Heterogeneity**

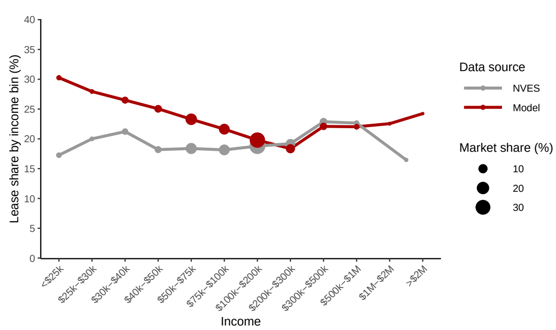
(a) Cumulative Share of Market



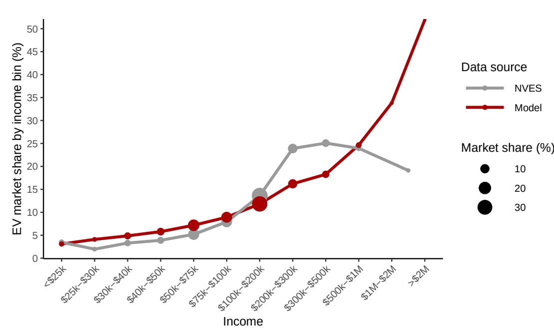
(b) Average Transaction Price



(c) Lease Propensity



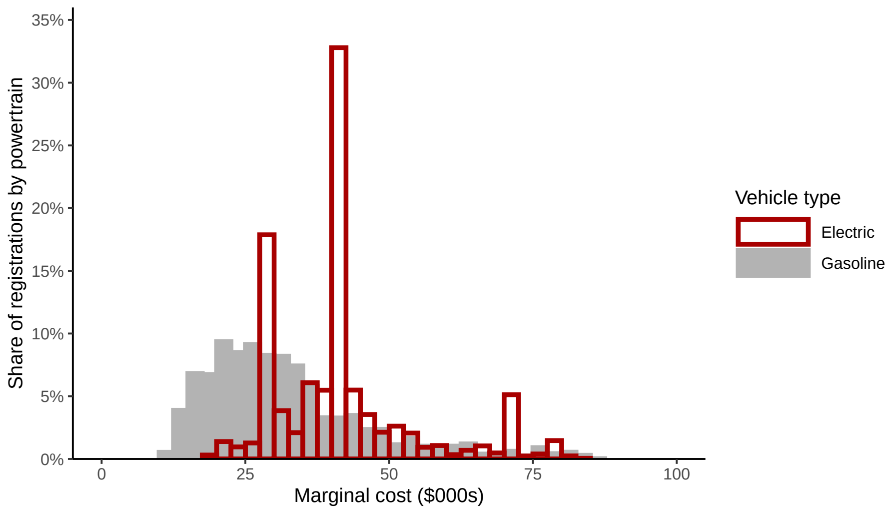
(d) EV Propensity



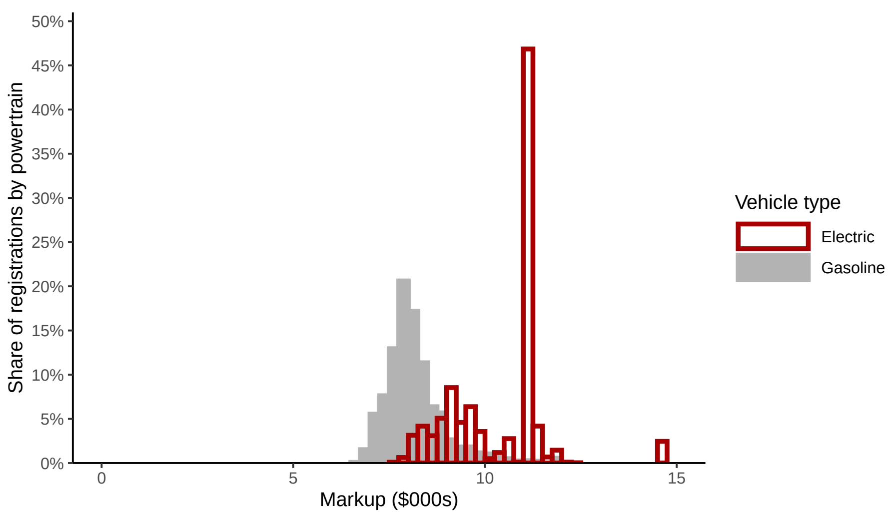
Notes: This figure presents a comparison across the full type distribution between model-implied outcomes and the NVES survey data. These four outcomes correspond to the four moments used in demand estimation. We do not target the full distribution, instead collapsing the data into a comparison between households above and below $300,000 in reported income as discussed in the text. The dot sizes reflect each bin’s estimated share of the vehicle market from the model.

Figure A17: **Distribution of Implied Marginal Cost and Markup for EVs and GVs**

(a) **Marginal Costs**



(b) **Markups**



Notes: This figure presents the distribution across submodels of purchase- and lease-specific marginal costs and markups implied by firms’ first-order condition in equation (8), weighting each choices registrations in July and August 2023. Markups are computed in the equilibrium where all EV subsidies are set to zero.