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

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Abstract

We study electric vehicle (EV) tax credits in the US Inflation Reduction Act (IRA), the largest climate policy in US history, with three goals. First, we provide the first ex-post microeconomic welfare analysis of this central component of the IRA. Event studies around changes in eligibility for EV tax credits find that short-run economic incidence falls largely on consumers. Additionally, domestic content restrictions on tax credits for purchased vehicles have driven enormous shifts to leasing. Our equilibrium model shows that compared to pre-IRA policy, IRA EV credits generated \$1.87 of US benefits per dollar spent in 2023, at taxpayer cost of \$32,000 per additional EV sold. Compared to scenarios with no EV credits, however, the IRA EV credits created only \$1.02 of benefits per dollar of government spending. Second, we characterize the gains from policies targeting heterogeneity in externalities across vehicles. We find that relative to uniform credits, differentiating credits across EVs according to their heterogeneous externalities would substantially increase policy benefits. Third, we quantify tradeoffs in the IRA EV credits between foreign and domestic welfare and between trade and the environment. We find that the IRA EV credits benefit the environment but undermine trade, since they decrease global carbon emissions but use profit shifting to decrease foreign producer surplus. A controversial IRA loophole that removes domestic content restrictions on tax credits for EV leases has negative domestic benefits.

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 bills 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, the Administration designed the IRA to protect domestic manufacturing, secure supply chains, and achieve political sustainability across elections. To achieve these objectives, the IRA relies heavily on uniform tax credits for low-carbon technologies made in the US and allied countries. Tax credits for electric vehicles (EVs) represent a central component of the IRA. Bistline, Mehrotra and Wolfram (2023) and the Committee for a Responsible Federal Budget (2023) project that the EV credits may cost the US government from \$70 to \$390 billion over a decade, representing up to half of the IRA's projected total tax credit spending.

The IRA's EV credits are one example of a larger set of vehicle electrification policies, which encourage substitution from gasoline vehicles (GVs) to EVs but less often distinguish among EVs. Across the US, China, Japan, the EU, and elsewhere, this effort includes EV purchase subsidies, sales targets, free charging, carpool lane access, and discounted tolls. Policy has long reflected heterogeneous externalities within GVs, but the IRA and many EV policies abstract from heterogeneous externalities within EVs. Switching from a Prius GV to a Cybertruck or Hummer EV, for example, supports vehicle electrification but may dramatically increase externalities.

The EV tax credits also offer a fascinating case study of combining climate and industrial policy, and more broadly using trade policy to benefit the environment. To encourage a transition to EVs while reducing China's dominance of manufacturing and battery supply chains, the IRA restricts tax credits under Section 30D of the US tax code to vehicles assembled in North America that contain a sufficiently large share of battery inputs from the US or allied countries (excluding China). As we discuss, these substantially prioritize US production, part of a longstanding "Buy American" federal policy goal that the Biden Administration has expanded. Equally generous credits to companies for leasing EVs under a new Section 45W of the tax code lack these restrictions, generating a "leasing loophole." Yablon (2023) summarizes tensions this has 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).

Motivated by these rapid policy developments, we use event study analyses and an equilibrium model of new vehicle supply and demand to study the IRA's EV tax credits, with three purposes. First, we assess the EV credits' impacts, including their distributional effects. Second, we use this setting to learn about optimal policy design for EVs with heterogeneous externalities. Third, we quantify tradeoffs that this case study 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 exploits a uniquely extensive combination of vehicle market data. We combine proprietary transaction-level dealership microdata from Cox Automotive, monthly national new vehicle registrations by submodel from Experian, aggregate supply conditions data from Edmunds, second choice survey data from Strategic Vision, registration microdata from the two states with the largest population and GDP (California and Texas), archival web scraping records for Tesla, original surveys we conducted with over 250 dealerships, administrative air pollution measurements for new GVs, and administrative credit eligibility from the US Treasury Department. These records allow a deeper analysis of clean vehicle tax credits, heterogeneity in EV externalities, and this combination of trade and environmental policy than has previously been possible.

We begin by describing externalities within EV and within GV submodels. For each vehicle, we calculate manufacturing CO_2 emissions; CO_2 and local air pollution emissions from driving; 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 2023a) and other marginal damages building on Holland et al. (2016). We find similar heterogeneity within EV submodels as within GV submodels, and substantial overlap in the EV vs. GV externality distributions. This striking finding conflicts with the prevailing approach of interpreting substitution from GVs to EVs (vehicle electrification) as the critical policy objective to decrease externalities, without focusing on which EVs consumers choose. For example, the 90th percentile submodel among EVs generates externalities of \$24,300 over its lifetime, while the 10th percentile submodel among EVs generates \$12,100 in externalities; the comparable statistics for GVs are \$27,100 and \$14,000.

To evaluate the EV tax credits' economic incidence, we use event study analyses to estimate how new vehicle prices changed as EV credit eligibility changed. Under Section 30D, qualifying EV buyers may receive \$7,500 income tax credits for buying eligible vehicles. EVs assembled outside of North America lost eligibility in August 2022. Many other vehicles lost eligibility in April 2023 with the implementation of battery sourcing requirements. The event study analyses find no statistically significant purchase price changes in the months after vehicles lost eligibility, and our confidence intervals rule out price decreases of more than about \$1,000. Because consumers received the tax credit post-purchase through individual income tax filings, this limited purchase price decrease implies that much of the credits' economic incidence was on consumers.

Our event study analysis also evaluates how the IRA EV credits affect purchase mode. Under the new Section 45W of the tax code, companies leasing vehicles could claim corporate income tax credits for leasing any EV, starting in January 2023. We measure lease prices as the present value of the down payment, monthly payments, and residual. We find that lease prices dropped relative to purchase prices in 2023. This finding implies substantial pass-through of the 45W credits to consumers who leased EVs. Driven by the decreased price of leasing relative to buying, our event study analysis also finds that EV markets shifted significantly toward leasing throughout 2023. In December 2022, leasing accounted for 15 percent of new EV registrations. By December 2023, this share had risen to 30 percent. Vehicles that lost 30D purchase credit eligibility in August 2022 had especially large shifts to leasing.

To study counterfactual scenarios and perform welfare analysis, we turn to an equilibrium model of vehicle supply and demand. The model uses a typical nested logit demand system with an exogenous choice set, constant marginal costs, and static Nash-Bertrand pricing, as in Goldberg (1995) and Goldberg and Verboven (2001). This framework is appropriate for predicting effects over a several-year horizon: long enough to ignore temporary inventory constraints, but short enough to ignore supply chain adjustments, entry of new models, or learning-by-doing effects. We design the demand system to have flexible substitution patterns on the four margins most important for evaluating EV tax credits: substitution across vehicle models, from buying to leasing, across vehicle classes, and from EVs to GVs. We calibrate the substitution parameters to match empirical moments from our event studies, second choice data, and price sensitivity estimates from Grieco, Murry and Yurukoglu (2024), although we also report results under alternative assumptions.

We find that replacing the IRA EV credits with no credits or pre-IRA credits has complex market and welfare effects. Repealing the IRA EV credits decreases EV registrations by 10 to 30 percent under pre-IRA or no credit counterfactuals, respectively, and decreases EV leasing by more than half. The IRA spends \$23,000 to \$32,000 per incremental EV sold, since only 23 to 33 percent of credits are marginal (i.e., additional). From the US planner's perspective, switching from no EV credits to the IRA's credits has a marginal value of public funds (MVPF) of 1 to 1.2. But replacing pre-IRA EV credits with the IRA EV credits has an MVPF of 1.9 to 2.1, which is higher partly since pre-IRA policy mostly subsidized foreign vehicles. We also find that an IRA repeal pits trade versus the environment. Repealing the IRA credits increases foreign firms' sales and foreign producer surplus, due to the IRA's domestic and allied content restrictions. But repealing IRA credits substantially increases CO_2 emissions.

We then compare the IRA EV tax credits to counterfactuals with tighter or looser trade restrictions, which largely close the leasing loophole. The leasing loophole itself performs poorly, with an MVPF of 0.4 to 0.8. The leasing loophole is not a cost-effective way to relax trade restrictions because, given our estimated substitution patterns, many buyers of foreign EVs would have alternatively bought a US EV. Thus, the leasing loophole transfers substantial producer surplus to foreign firms while generating little incremental EV takeup.

We also compare the IRA EV tax credits to alternative policies that maximize total surplus in our framework, while holding the Section 30D credit eligibility list fixed. We show formally that the constrained optimal uniform or differentiated subsidy equals the sum of three terms: the net distortion (markup minus negative externality); an adjustment for indirect substitution from non-subsidized vehicles weighted by those vehicles' net distortion; and profit-shifting away from foreign firms. We obtain an analogous result for optimal uniform subsidies, with demand-response weighted averages across models of the above three terms.

We find that first-best policy would tax all vehicles, because we estimate that all vehicles have negative externalities larger than their markups. However, if GVs cannot be taxed, it is optimal to subsidize EVs to induce substitution from GVs, which on average have higher externalities. Under the restriction of using a uniform EV subsidy for both purchases and leases, we find that a uniform EV subsidy of $6,355 maximizes US total surplus if the government can raise funds via non-distortionary lump-sum taxation. The net distortion accounts for 36 percent of the optimal subsidy, the indirect substitution for 14 percent, and the profit shifting component for 50 percent. The optimal uniform subsidy in our model is close to the IRA's actual uniform subsidy, although imposing that optimal uniform subsidy instead of the IRA EV tax credits increases US total surplus by around $1 billion annually. However, when accounting for the deadweight loss of taxation (i.e., assuming a marginal cost of public funds of 1.4) we find an optimal uniform subsidy much further below the IRA's actual value.

Our estimated externalities vary substantially across EV submodels due to heterogeneity in EV weight and electricity use per mile. Thus, we find that model-specific differentiated EV subsidies reduce deadweight loss relative to a uniform EV subsidy, increasing US total surplus by $1 to $2.5 billion annually. Compared to no subsidies, uniform subsidies achieve 57 percent of the domestic welfare benefit of subsidies differentiated across EVs. Thus, in our analysis, the IRA credits leave considerable social value on the table by using uniform subsidies for vehicles with different externalities.

Our paper has several important limitations. Whereas our analyses describe the short-to-medium run outcomes, they do not describe effects of EV tax credits over the long-term, when automakers might adjust supply chains, develop new models, or benefit from learning-by-doing. Such long-term effects were important motivations for the IRA but would be difficult to quantify credibly. We also do not consider how other countries might respond to US trade restrictions by imposing their own restrictions. Our short- to medium-run analyses are still important given ten-year budgeting horizons in the US Congress, a two- to six-year election cycle, and the rapid developments in EV policies and investments.

We contribute to a nascent literature evaluating the IRA, and more broadly to analyses of US tax credits for clean vehicles. This literature includes policy overviews (Bown 2023; Buckberg 2023), reduced-form and structural evaluations of previous state and federal tax credits (Chandra et al. 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 et al. 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 recent working papers model long-run benefits: Linn (2022) models US EV credits in a model with endogenous entry of new vehicles, Head et al. (2024) model reallocation of EV supply chains in response to the IRA, and Barwick et al. (2023) and Barwick et al. (2024) focus on the effects of Chinese EV tax credits in a model with learning-by-doing. Our finding that many EV credits are inframarginal echoes Arkolakis and Walsh (2023)'s analysis of the IRA's solar and wind electricity subsidies using ex ante data. Bombardini et al. (2024) and Cox and Acosta (2023) study broader costs of Buy American provisions in federal procurement. Relative to those bodies of work, we provide the first ex post empirical microeconomic welfare evaluation of the IRA's EV tax credits, which are both one of the most significant environmental policies in US history and also a leading example of US trade and environmental policy. Our estimate of the additionality of EV subsidies echoes recent estimates of environmental policy additionality in disparate settings (Aspelund and Russo 2024; Chen et al. 2024).

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 components due to profit shifting versus distortions. Additionally, we distinguish the role of profit shifting in welfare analysis of the actual IRA EV credits. Unilateral trade policy in imperfectly competitive markets can transfer producer surplus from foreign to domestic firms (Brander and Spencer 1981, 1984; Venables 1985; Bagwell and Staiger 2012). Quantitative models of trade and the environment typically assume perfect competition so cannot analyze profit shifting (Costinot et al. 2016; Larch and Wanner 2017; Shapiro 2021; Kortum and Weisbach 2021; Caliendo et al. 2024); the fewer trade-environment models with monopolistic competition do not directly analyze profit shifting (Nordhaus 2015; Shapiro and Walker 2018; Farrokhi and Lashkaripour 2024), though Levaggi and Panteghini (2023) provide results in a simple model of multinational firms. Copeland and Taylor (2003), Cherniwchan, Copeland and Taylor (2017), Copeland, Shapiro and Taylor (2022), Balboni and Shapiro (2024), and Desmet and Rossi-Hansberg (2024) provide broader overviews of the trade-environment literature, with little direct discussion of profit shifting. Similarly, research on "issue linkage" of tying human rights, environmental quality, or other social objectives to trade policy has little role for profit shifting (Rodrik 2014; Maggi 2016). Since Buchanan (1969), research has emphasized that optimal environmental taxation in concentrated industries differs from the Pigouvian benchmark due to market power. A few studies focus on 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 be especially pertinent to trade-environment issues because polluting industries have high levels of trade exposure, returns to scale, shipping costs, capital intensity, and other drivers of concentration (Copeland, Shapiro and Taylor 2022; Shapiro 2024). Our discussion of these topics contrasts 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.

Third, we contribute to the broader literature on auto market environmental regulation, including Goldberg (1998), Berry et al. (1999), Bento et al. (2009), Fowlie, Knittel and Wolfram (2012), Jacobsen (2013), Jacobsen and van Benthem (2015), Knittel and Sandler (2018), and Gillingham, Ovaere and Weber (Forthcoming). 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) 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. These elements prove important, as distortions from market power and international profit shifting together constitute a substantial portion of the constrained optimal subsidies we calculate.

The remaining sections 2–8, respectively, present the policy background, data, descriptive facts, event studies, structural model, counterfactuals, and conclusion.

2 Policy Background

2.1 Electric Vehicle Markets

An electric vehicle is defined as any vehicle with an electric motor and a plug. This includes plug-in hybrid electric vehicles (PHEVs), which have both an electric motor and a gasoline engine, and battery electric vehicles (BEVs), which do not have 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 from our analysis, as they accounted for only 0.02 percent of new vehicle sales in 2022 and 2023.

EVs represented 18 percent of global new light-duty vehicle sales in 2023, up from 2 percent in 2018 (IEA 2024). China dominates the EV market: 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).

US political leaders have responded to China's dominance and EV growth by emphasizing domestic manufacturing, industrial policy, and secure supply chains. For example, National Economic Council director Brian Deese has said that "[we envision] a twenty-first-century American industrial strategy—a strategy to strengthen our supply chains [and] rebuild our industrial base" (Atlantic Council 2021). Similarly, National Security Adviser Jake Sullivan has 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 (2022) 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 lets us observe one piece of information about the planner's objective function, which suggests that US policymakers may perceive non-zero disutility from foreign climate change damages. In regulatory design and evaluation, the US government uses a global social cost of carbon (SCC), including damages to all foreign countries (US EPA 2023a).[1] At the same time, the IRA's use of domestic and allied content restrictions implicitly values domestic producer surplus and labor earnings, at the expense of foreign surplus.

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 Investment Act (ARRA) limited full eligibility to the first 200,000 EVs each manufacturer sold; 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 reachinmg the cap.

Both individual and corporate taxpayers may receive the 30D credits. For example, a business can claim the credit for buying vehicles for its motor pool or for buying a vehicle to lease to an individual.

The IRA, which became law on August 16, 2020, 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, or $150,000 for all other taxpayers, starting January 1, 2023.

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

First, starting August 17, 2022, vehicles had to undergo final assembly in North America. This excluded the European and Asian models colored in red. We refer to these submodels as 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. Also starting on that date, 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 and Mercedes-Benz EQS as well as Tesla models S and X.

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

Third, starting April 18, 2023, the policy added a battery component and minerals requirement on top of the North American assembly requirement. We refer to these submodels as the Excluded/Reduced April 2023 group. The policy 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 are set to increase further in future years. In 2023, these requirements reduced or fully eliminated credits for the Ford, Jeep, Rivian, Audi, BMW, and Nissan models, colored in orange.

The IRA also established a new "Commercial Clean Vehicle Credit" under Internal Revenue Code Section 45W, starting January 1, 2023. Section 45W also offers \$7,500 credits for new plug-in EVs under 14,000 pounds, and larger credits for larger vehicles. All EVs qualify for 45W credits, with no final assembly, battery content, or buyer income requirements. In late December of 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 buyer income or vehicle eligibility restrictions, could instead *lease* that same vehicle, and the leasing company would qualify for the 45W credit. While the IRA specifies that the 30D and 45W credits will end after 2032, it does not cap credits before then.[2]

3 Data

3.1 Main Datasets

This section describes data; Appendix A 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) lack different trims or powertrains.

We purchased nationwide new vehicle registrations by submodel and month of registration from Experian. We separately observe purchases and leases. The Experian data let us measure lease share as the ratio of leases to total registrations. We include only registrations for personal use or lease, excluding other sales to businesses, and we exclude heavy-duty vehicles.

We observe price data from three sources. First, we have dealership transaction microdata from Cox Automotive. For purchases, we observe the vehicle price, excluding taxes, net of any rebates. For leases, we observe lease lengths, annual percentage rates (APR), any rebates, and the

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

resulting monthly payment amounts. The Cox data include 6.8 million new vehicle transactions in 2022 and 2023, representing 31 percent of total national transactions in those years. Brand-level coverage rates vary but mostly range from 20 to 50 percent, while state-level coverage rates range from about 10 to 30 percent; see Appendix Figure A1. Cox has no coverage of new vehicle sales by Tesla, Rivian, and Lucid, as they sell directly to consumers instead of through dealerships.

Second, we augment the Cox data by collecting Tesla monthly purchase and lease prices for base model configurations. We obtain the Tesla data by scraping online sources such as the Tesla website (via the Internet Archive), contemporaneous reports of pricing, and historical price data openly collected by Tesla enthusiasts (Appendix A provides more details). Third, we use registration-level microdata from the California Department of Motor Vehicles (DMV). Dealerships report the prices, which include the full price excluding sales tax, license fees, or financing costs. For leases, the California data have no information on rebates or other contract terms besides the reported price that the lease reflects. The California and Cox purchase prices have a correlation of 0.99 at the submodel-by-month level.

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. Let s index the monthly payments, which consumers make at the beginning of each month. 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 and p_{kt} in the Cox 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). The lease price equals

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

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.

In the submodel-by-month panel, the purchase price and lease price variables represent the mean across transactions. Since the California data include direct-to-consumer brands like Tesla, we use California data for purchase price. Since Cox has detailed information on lease terms, we use Cox for lease price. The relative lease price variable equals the submodel-by-month difference between purchase price and lease price in Cox data, augmented with the scraped Tesla data.

Appendix Figure A2 shows the full list of EV submodels and the months in which they appear 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. 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, when monthly registrations fall below half of the submodel's sample average. Appendix Figure A3 illustrates the phase-in and phase-out periods that we exclude. We also exclude any observations with fewer than 25 registrations. Additionally, we exclude any purchase or lease price observations based on fewer than 10 transactions.

Table 1 presents descriptive statistics for the submodel-by-month dataset. Our data cover a total of 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.

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 indexes. 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. For each previous or subsequent month, we then recursively add the sales-weighted mean change for all submodels available in both months.[3]

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 time 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; Tom Pritchard 2023; The Internet Archive 2023).

Second, in summer 2023, we surveyed US dealerships to determine EV market wait times, prices, and qualitative characteristics. 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.2 provides details.

Third, to identify substitution patterns in our demand model, we use second choice data from the New Vehicle Experience Survey (NVES), collected by the company Strategic Vision. Strategic Vision surveys a large sample of US new vehicle buyers soon after their purchase, 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. We have 273,290 survey responses from the 2022 and 2023 surveys.

Finally, we assume that vehicles impose four externalities: (i) manufacturing CO_2 emissions, (ii)

[3] Formally, 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

$$\bar{x}_t = \frac{\sum_k \bar{q}_k x_{k0}}{\sum_k \bar{q}_k} + 1\,(t > 0) \sum_{r=1}^{t} \frac{\sum_k \bar{q}_k \left(x_{k,r} - x_{k,r-1}\right)}{\sum_k \bar{q}_k} + 1\,(t < 0) \sum_{r=-1}^{t} \frac{\sum_k \bar{q}_k \left(x_{k,r} - x_{k,r+1}\right)}{\sum_k \bar{q}_k}. \qquad (2)$$

As described in the text, x_{kt} is missing for some kt, so the sums over k implicitly include only non-missing observations.

CO_2 and local air pollution emissions from driving, (iii) fatal accidents, and (iv) fiscal externalities from explicit or implicit taxes on gasoline and electricity. For CO_2 emissions from the value chain of manufacturing vehicles, we use estimates from Argonne National Labs (Kelly et al. 2022), which distinguishes three powertrains (BEV, PHEV, GV), but has no heterogeneity across submodels. For the 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. (2016) with US EPA (2024) exhaust test records and fuel efficiency. 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 and 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). We inflate all values to July-August 2023 dollars using the CPI for all Urban Consumers (Federal Reserve Bank of St. Louis, 2024a). We assume that 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 (2023a). The "domestic SCC" uses domestic (instead of global) damages from CO_2 emissions, equal to $28 per ton, computed using the ratio of the United States SCC to global SCC from Ricke et al. (2018) times the global SCC. Appendix A.1 provides additional details.

4 Descriptive Facts

Several descriptive facts play important roles in developing and interpreting our empirical results.

Tesla dominates the US EV market. Panel (a) of Figure 2 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.

EV prices peaked in mid-2022. Panel (b) of Figure 2 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 3 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 been at the dealership for about 20 days, while the mean vehicle sold in July 2023 had been at the dealership for over 50 days. 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 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 a month for 94 percent of EVs sold via dealerships; 90 percent of EVs were available immediately.[4]

A majority of EV buyers have incomes below the IRA's 30D limit. The expected effects of the IRA's Section 30D credits depend on what share of buyers have incomes below the that section's limits of $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 A4. The IRS Statistics of Income (SOI) data show that 54 percent of taxpayers who claimed 30D credits in 2021 had Adjusted Gross Income under $200,000.

Assembly locations shifted little after the 30D eligibility requirement. Most vehicles excluded from eligibility have not changed their assembly sites, remaining in the same locations from before August 2022 to late 2023. A notable exception is the Volkswagen ID.4, which transitioned from assembly in Germany to Volkswagen's Chattanooga, Tennessee plant, though this shift began before the IRA's passage. Both Hyundai and Kia have announced and begun constructing US facilities for their electric vehicles. Hyundai's investment in Georgia was announced before the IRA, while Kia's Georgia facility was announced in mid-2023.

The EV market share is growing but the domestic assembly share is not. Figure 4 shows US trends that have resulted from the IRA credits plus other market forces. Panel (a) shows that the EV share of new vehicles rose from 6.9 percent in the first quarter of 2022 to 12 percent by 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 period. Of course, this graph does not show what would have happened without the IRA. For example, foreign manufacturers introduced a disproportionate number of new EV submodels from late 2022, likely independently of the IRA, since submodel introduction requires a long lead time. Without the IRA, this 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 4 shows that about 90 percent of EVs assembled in North America are US-assembled. The share of US-assembled as proportion of North American-assembled is lower for GVs, at about two-thirds. While the Section 30D EV credits require North American assembly, these data show that in practice this requires US assembly, making the credits 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 A5 provides one example). Several dealers in our survey also proposed a strategic transaction to evade Section 30D restrictions—these dealers proposed leasing the vehicle, then very soon afterwards the dealer 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

[4] The corresponding wait times not weighted by market share are 91percent under a month and 86percent immediately. Our dealer survey, including these statistics, excludes Tesla and Rivian since these brands sell direct to consumer.

or MSRP restrictions. We are not aware of any media, government, or academic evidence mentioning the existence of this "loophole within a loophole." We investigated the statistical prevalence of this strategic evasion in the Texas registration data. We estimate that it exists but is quite rare, so we do not pursue it further. (Appendix B.1 provides details)

EVs have somewhat lower externalities than GVs. Table 2 summarizes our lifetime submodel-level externality values by powertrain. Using the global SCC, the mean EV imposes about $16,000 in lifetime negative externalities, while the mean GV imposes $19,200 in negative externalities. It may be surprising that the difference between EVs and GVs is relatively small. The table rows show that while EVs do have $6,500 lower CO_2 externalities from driving, they have higher other non-fiscal externalities—higher CO_2 externalities from manufacturing ($900), higher local pollution externalities ($1,900), and higher accident externalities due to EVs' greater weight ($2,300), though more positive fiscal externalities ($1,700). More surprisingly, valued at the US SCC, the mean EV has 30 percent *higher* negative externalities than the mean GV, partly because the mean EV is about 30 percent heavier than the mean GV and because GVs have lower local pollution emissions. Table 2 also shows that environmental externalities from CO_2 meaningfully exceed environmental externalities from local air pollution. While our analysis measures both sets of externalities, for this reason our subsequent discussions of the "environment" primarily reflect CO_2.

EVs have large heterogeneity in externalities and similar heterogeneity as GVs. Figure 5 displays 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 appears similar within EVs and within GVs. Not shown in the figure is one other type of heterogeneity: the mostly foreign-assembled vehicles that the 30D credits exclude have slightly larger negative externalities than 30D-eligible submodels ($608 on average), a fact that affects our evaluation of trade restrictions in Section 6.

Appendix Table A1 shows three measures of the dispersion in externalities across submodels corresponding to the histograms in Figure 5—the standard deviation; 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. The standard deviation is modestly higher for GVs, partly since the mean externality is higher, but the coefficient of variation and interdecile ratio have similar magnitude for EVs as for GV, and the statistical tests fail to reject that these values are equal for the two powertrains. This finding also applies for several components of externalities individually.

This finding matters because numerous policies around the world focus on moving consumers from GVs to EVs—"vehicle electrification" is an omnipresent climate policy goal. Such policies largely ignore whether consumers purchase high- or low-externality EVs. The finding has some potentially general implications. Policies that make consumers substitute from clean GVs to dirty

EVs (e.g., Priuses to Cybertrucks) can increase externalities. 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 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 asks two empirical questions about the short-run effects of EV tax credit eligibility changes. First, how much economic incidence has been on consumers versus producers? Second, how elastic is substitution between purchases and leases? To answer these questions, we exploit variation over time in eligibility rules for both Sections 30D and 45W using event study designs.

5.1 Methodology

Our event study analyses consider three outcomes: purchase prices, relative lease prices, and lease shares. We also estimated effects on registration quantities, but the estimates were economically imprecise and potentially related to other market trends; see Appendix C.3. For each outcome, we present two graphical analyses: descriptive trends in the fixed-weight index and event study estimates. The latter use two-way fixed effects regressions with GVs as controls. In market equilibrium, price changes for any vehicle can affect prices and sales of 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 an outcome variable for submodel k in month t: purchase price, relative lease price (i.e., lease price minus purchase price in the Cox data), lease share, or natural log of registrations. 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 C_k represent the absolute value of the change in tax credit available to submodel k, divided by \$7,500. For example, a vehicle that becomes eligible for the full \$7,500 tax credit has $C_{kt} = 1$, and a vehicle where eligibility falls from \$7,500 to \$3,730 has $C_{kt} = 0.5$. We define ϕ_j and ν_t as submodel and month-of-sample fixed effects. We estimate event study graphs using

$$y_{kt} = \sum_{e} \sum_{s \in \mathcal{S}^e} \gamma_s^e C_k \cdot 1\{t - s = t^e\} + \phi_k + \nu_t + \varepsilon_{kt}. \tag{3}$$

We cluster standard errors by model 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 it is available. Unweighted results would disproportionately reflect low-volume submodels and the exact definition of a submodel.

We considered several alternative specifications. “Doubly robust” estimates where the GV control group is reweighted to match the EV pre-IRA average price give very similar estimates; see Appendix C.2. Alternative specifications using only EVs as controls give considerably noisier estimates that are mostly not statistically distinguishable.[5]

5.2 Purchase Prices and Economic Incidence

We first consider purchase prices as a way to learn about economic incidence. If purchase prices remain unchanged when a vehicle's eligibility changes, this implies that consumers bear the full economic incidence, since buyers can later claim the entire 30D tax credit on their individual income taxes.[6]

In theory, several forces govern economic incidence. First, incidence reflects the relative elasticity of supply and demand. Figure 3 showed that inventory was tight in 2022, but supply became more elastic in 2023. Second, not all consumers qualify for the 30D credits. Tighter eligibility restrictions reduce aggregate demand shifts, attenuating price changes and thus increasing incidence on eligible consumers. Third, adjustment costs and time lags in decisionmaking could attenuate or delay price changes. Fourth, it may take time for consumers to become fully aware of recent EV credit eligibility changes, although the value of learning this information is high. Fifth, even if mean purchase prices remain unchanged, producers may bear some incidence if prices change differently for firms with different market power (Weyl and Fabinger 2013).

The fixed-weight purchase price indices in Panel (a) of Figure 6 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 2. 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 event study coefficients γ_s^e from equation (3) for each eligibility group in Panel (b) of Figure 6 also suggest that EV tax credit eligibility had limited effects on purchase prices. The patterns closely match Panel (a). The left sub-panel shows that the 95 percent confidence intervals rule out that prices for the submodels that lost eligibility in August 2022 dropped more than \$500 to \$1,000 September–December 2022 relative to August 2022, although prices do drop in early 2023. The right sub-panel shows the 95 percent confidence intervals rule out that the Excluded/Reduced April 2023 group's prices dropped more than about \$2,000 relative to April 2023. We do not consider event studies for the groups that changed eligibility in January 2023 because those are immediately coincident with the large Tesla-led price cuts, related to broader market trends in that period.

[5] New difference-in-difference approaches focus on addressing staggered treatment timing (Roth et al. 2023; Roth 2024), which is not relevant in our setting because equation (3) estimates a separate set of coefficients $\{\gamma_s^e\}$ for each eligibility group.

[6] In January 2024, after our data, buyers became able to claim the credit at point of sale.

Regression estimates that restrict the coefficients to be equal across the submodels that lost eligibility in August 2022 and April 2023 also suggest that consumers bore the bulk of the short-run incidence of losing Section 30D credit eligibility. 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. Thus, when eligibility changes exclude these vehicles from $7,500 buyer-side income tax credits in August 2022 or April 2023, we reject the hypothesis that purchase prices drop by more than a small fraction of that amount.

5.3 Relative Lease Prices

We next analyze 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, both because the previous subsection makes predictions about this relative price and because this can difference out potentially confounding pricing trends.

Recall that both 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 thus expect that newly eligible firms would reduce the price of leasing relative to purchasing by roughly $7,500, the amount of the tax credit.

Panel (a) of Figure 7 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 Tesla and GM, 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. Tesla and GM 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 7 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, Tesla and GM 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 A6. 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.

5.4 Lease Shares

Finally, we consider how the IRA's EV credits affect lease shares. Purchase-to-lease substitution matters because it reflects the effects of the leasing loophole. If many additional consumers are willing to lease, then the leasing loophole has large effects and generates less deadweight loss. If few additional consumers are willing to lease, then the loophole has limited effects, and any quantity effects we do see reflect larger deadweight loss.

One might expect an increase in EV lease shares in 2023 for two reasons. First, a price effect—as shown in the previous section, relative lease prices decreased for some EVs in 2023. Second, a buyer eligibility effect—when the 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 8 presents the fixed-weight indexes of lease shares for the same three groups plotted in Figure 7. For Tesla and GM, 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.

Panel (b) of Figure 8 presents the event study estimates, where we again define the "event" as happening in January 2023. Consistent with Panel (a), we see a 45 percentage point lease share increase for the Excluded August 2022 group compared to the GV trend since December 2022, little change for Tesla and GM until the very end of 2023, and a 20 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 wanted to lease.

6 Equilibrium Model

The event study analyses of the previous section analyze data from up to 18 months after the IRA began, which we interpret as the short run. This section describes an equilibrium model of vehicle supply and demand, similar to Goldberg (1995). We incorporate a purchase and lease option, which allows us to evaluate the consequences of the policy differences between purchases and leases. While we target the model to match the purchase-lease-substitution from the event studies, we also target other moments from existing estimates and consumer surveys, and we design the model to abstract from long-run changes like factory investment, so we interpret this equilibrium model as describing short- to medium-run IRA impacts. We combine our model with a welfare framework that allows us to evaluate the effects of alternative policies, as well as to compute optimal policy within our framework, under various constraints and planner objectives.

6.1 Model Setup

Demand We assume a four-level nested logit demand system to capture four margins of substitution that are relevant for evaluating EV purchase and lease credits: substitution from purchases to leases, across models within a vehicle class, across vehicle classes, and from EVs to GVs. 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 vs. lease). Consumers can purchase any submodel and can lease most submodels, meaning some do not offer 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.[7] There are J total inside goods, plus we include $j = 0$ to index the outside option (e.g., buying a used vehicle).

There are M consumers in the market indexed by i. Each consumer selects the choice that maximizes their utility. Let p_j represent the purchase price or lease price, and τ_j is the 30D tax credit. Because most consumers satisfy the income requirements and we focus on trade restrictions, we assume that all consumers qualify for the tax credit.[8] Consumer i receives the following indirect utility from choice j:

[7]In our data, there are nine such classes with enough registrations to include in the estimation. Within GVs there are SUVs, sedans, pickup trucks, minivans, and coupes/convertibles. Within EVs there are SUVs, sedans, pickup trucks, minivans. Informed by the patterns in the second choice surveys, we combine hatchback vehicles with sedans and crossover vehicles with SUVs.

[8]Abstracting from income heterogeneity has the advantage that it makes conditions for uniqueness easier to establish. In experiments with income heterogeneity we encountered multiple equilibria.

$$U_{ij} = \xi_j - \alpha \left(p_j - \tau_j\right) + \epsilon_{ij}, \tag{4}$$

Here α represents the marginal utility of money, ξ_j captures all vehicle attributes other than the price, and ϵ_{ij} is an idiosyncratic preference distributed type-1 extreme value. We normalize $U_{i0} = \epsilon_{i0}$ for the outside option. We use bold typeface to indicate vectors, so $\boldsymbol{\xi}$ is the vector of ξ_j parameters.

Appendix Figure A11 illustrates the nesting structure. The nested logit model allows 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 is what generates correlation in preferences across choices. The dispersion of these coefficients is captured by three parameters $\left\{\sigma^k, \sigma^c, \sigma^g\right\} \in [0, 1)$.[9] Then ϵ_{ij} takes a standard nested logit form:

$$\epsilon_{ij} = \zeta^g_{ig(j)} + \left(1 - \sigma^g\right) \zeta^c_{ic(j)} + \left(1 - \sigma^g\right) \left(1 - \sigma^c\right) \zeta^k_{ik(j)} + \left(1 - \sigma^g\right) \left(1 - \sigma^c\right) \left(1 - \sigma^k\right) \tilde{\epsilon}_{ij}, \tag{5}$$

where $\tilde{\epsilon}_{ij}$ is i.i.d. type-1 extreme value. To be consistent with random utility maximization, we must have $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$ (McFadden 1978). If $\sigma^k = \sigma^c = \sigma^g = 0$, then this reduces to the standard logit model. As the dispersion parameters grow toward 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 to purchase a submodel which is an EV sedan. 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.

Under these assumptions, the market demand for any choice can be expressed in terms of conditional shares

$$q_j = s_{j|k(j)} s_{k(j)|c(j)} s_{c(j)|g(j)} s_{g(j)} \times M \tag{6}$$

where, for example, $s_{c(j)|g(j)}$ represents the conditional market share of choice j's class within its powertrain and $s_{g(j)}$ is the unconditional market share of j's powertrain (see Appendix D.1). Then, the substitution between any two choices j and r can be compactly expressed in terms of the definitions above as

[9] Cardell (1997) and Galichon (2022) provide more details on this formulation of the nested logit model. In particular, Galichon (2022) derives using the representation in equation (5) the exactly structure of the correlation across choices. In our setup, for any two choices j and r,

$$corr(\varepsilon_{ij}, \varepsilon_{ir}) = 1 - \left[(1 - \sigma_g)^{\delta_{g(j),g(r)}} (1 - \sigma_c)^{\delta_{c(j),k(r)}} (1 - \sigma_k)^{\delta_{k(j),k(r)}}\right]^2$$

where $\delta_{a,b}$ is the Kronecker delta.

$$\frac{\partial q_j}{\partial p_r} = \alpha s_j \Bigg[s_r + \left(\frac{1}{1-\sigma^g} - 1\right) s_{r|g(j)} \delta_{g(j),g(r)} + \left(\frac{1}{1-\sigma^c} - \frac{1}{1-\sigma^g}\right) s_{r|c(j)} \delta_{c(j),c(r)} \\ + \left(\frac{1}{1-\sigma^h} - \frac{1}{1-\sigma^c}\right) s_{r|k(j)} \delta_{k(j),k(r)} - \frac{1}{1-\sigma^k} \delta_{j,r} \Bigg] \times M \tag{7}$$

where $\delta_{a,b}$ is an indicator function taking on 1 if $a = b$ and 0 otherwise. (For example, if j and r are both EVs, then $\delta_{g(j),g(r)} = 1$.) Equation (7) shows how, when the condition holds that $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$, we see increasing substitutability between choices that share a nest.

Supply Auto manufacturing firms indexed f each offer a set of submodel-by-transaction type choices $\mathcal{J}_f$. Firms set their price vector $\boldsymbol{p_f}$ to maximize profits in static Nash-Bertrand competition.[10] The terms $\boldsymbol{p}$ and $\boldsymbol{\tau}$ represent the vectors of prices and 30D credits available for all choices, κ_j represents the 45W credit available to firms for leasing choice j, and $q_j\left(p; \boldsymbol{p}_{-j}, \boldsymbol{\tau}\right)$ represents choice j's total quantity demanded from equation (6) 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 profit maximization problem for all products in its portfolio, $\mathcal{J}_f$:

$$\max_{p_{j\, j\in\mathcal{J}_f}} \sum_{j\in\mathcal{J}_f} (p_j - c_j + \kappa_j) \cdot q_j\left(p_j; \boldsymbol{p}_{-j}, \boldsymbol{\tau}\right) \tag{8}$$

Firm f's first-order condition with respect to an arbitrary choice j in $\mathcal{J}_f$ is:

$$[p_j]: \quad q_j + \sum_{r\in\mathcal{J}_f} (p_r - c_r + \kappa_r) \frac{\partial q_r}{\partial p_j} = 0 \tag{9}$$

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 (6) and taking prices of competitor firms as given has, for each j it owns, a best response p_j that satisfies equation (9) in the pricing game and is consistent with the price vector $\boldsymbol{p}$. Nocke and Schutz (2018) show that a unique Nash-Bertrand pricing competition equilibrium exists with nested logit demand and multi-product firms whenever each firm supplies products only in one of the nests. Our baseline model does not satisfy this sufficient condition for uniqueness, though in practice we do not encounter multiple equilibria in estimation. We therefore

[10] We assume no interactions with the federal fuel economy and greenhouse gas emission standards. Since automakers had a large bank of compliance credits in 2023 (US EPA 2023b), the standards did not bind for that year alone, but instead the EPA designed them to bind over a longer future period. This assumption would exactly reflect reality if a future administration either set non-binding standards or set future stringency to equate marginal benefits and marginal costs of future compliance. 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.

also consider for robustness a version 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 alternative version of competition satisfies Nocke and Schutz (2018)'s conditions for uniqueness.

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 three sets of parameters: the vector of non-price attributes $\boldsymbol{\xi}$; the price response parameter α and three nested logit parameters $\left\{\sigma^k, \sigma^c, \sigma^g\right\}$; and the vector of marginal costs $\boldsymbol{c}$. First, for given values of $\left\{\alpha, \sigma^k, \sigma^c, \sigma^g\right\}$ and observed market quantities q_j, we back out the 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 $\left\{\alpha, \sigma^k, \sigma^c, \sigma^g\right\}$ that match a 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 vector of first-order conditions from equation (9).

Before estimating parameters, we make the following assumptions. Our baseline scenario considers the market as of July and August 2023, partly reflecting our dealership survey and statistical evidence suggesting supply chain constraints relaxed by this period. The choice set includes the vehicles available and IRA credit eligibility as in those months. Additionally, we set market quantities q_j equal to six times their total for July plus August, representing annualized values. Furthermore, we assume that each of the 131 million US households purchases a vehicle every six years as in Coşar et al. (2018), giving a total market size of 21.9 million households per year.

In the second step, we find $\left\{\alpha, \sigma^k, \sigma^c, \sigma^g\right\}$ that match four empirical moments, summarized in Table 3. We match these moments jointly, but discuss them sequentially. 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 monthly time-series data partly reflects supply constraints. In Appendix Table A5, we consider sensitivity to an alternative value of -4. Second, we match the effect on lease shares estimated in Section 5. Specifically, 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 match the simulated effect of that lease price decrease on lease shares for that group of models. Intuitively, these first two moments are jointly informative about α 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.

Third and fourth, we match two second choice moments from the NVES data: 52 percent of EV owners report another EV as their second choice and 33 percent of EV owners report another EV within the same segment as their first choice. These two moments are jointly informative about σ^c and σ^g, the correlation in preferences within a class and powertrain.

Table 4 presents the scalar parameter estimates. Since we have as many moments as parameters to estimate, we match the targeted moments exactly. Our methodology does not impose the requirement that $1 > \sigma^k \geq \sigma^c \geq \sigma^g \geq 0$ but our estimates satisfy that condition, so our demand system is consistent with utility maximization.

While we only target second-choice moments from the EV side of the market, the second choice shares from the model and the data – an untargeted moment – are relatively well aligned. Our estimated model implies that 94 percent of GV owners choose another GV as a second choice, compared to 97 percent in the NVES. Appendix Figure A12 shows the full substitution matrix between our nine-by-nine different powertrain-segment combinations in model and the data. The correlation between the two is 0.74 (and 0.88 when weighting cells by first-choice market share).[11] Our estimates also imply an aggregate new vehicle demand elasticity of -1.4. Berry, Levinsohn and Pakes (2004), Grieco, Murry and Yurukoglu (2024) and the empirical evidence in Allcott et al. (2023) suggest comparable values.[12]

We estimate all marginal costs to be positive. Given marginal costs, we estimate the following share-weighted mean markups: $9,100 for EVs (17 percent of price) and $8,400 for GVs (20 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. The dispersion of implied markups across submodels ranges from $7,600 to $10,800, with the largest markups for Tesla; see Appendix Figure A13.

Finally, we compare our model-implied pass-through to the regression estimate in Appendix Table A2 by simulating a removal of 45W lease credits to suppliers. The model implies complete pass-through of the $7,500 lease credit to consumers among the Excluded August 2022 group of vehicles, as compared to our event study estimate of $5,677 (95% CI: [$4,055, $7,299]) in Appendix Table A2.

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, denoted by $CS(\boldsymbol{p}, \boldsymbol{\tau})$. We compute producer surplus as the sum

[11] We also calculated model fit to the miles per gallon equivalent (MPGe) for GVs and EVs of second-choice vehicles. Among GV buyers who consider a second choice, the second choice has actual mean MPGe of 27.1 and model-estimated mean of 30.7. Among EV buyers who consider a second choice, the second choice has actual mean MPGe of 66.7 and model-estimated mean of 64.0. While these statistics suggest good fit to this non-targeted moment, this moment is closely related to choice of powertrain and mean MPG within each powertrain, so the good fit is perhaps unsurprising.

[12] In our sensitivity to an own-price demand elasiticity of -4, the aggregate demand elasticity is -1.1.

of producer profits given markups, μ_j.[13] Subsidies provided by the government have a fiscal cost that depends on the marginal cost of raising public funds, η. Externalities arise from the production and use of choice j and consist of carbon and non-carbon damages under an assumed social cost of carbon, $\phi_j = SCC \times \phi_j^{CO_2} + \phi_j^{Other}$. Appendix A.1 provides details of how we calculate these externalities.[14]

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

$$W(\boldsymbol{\tau}, \boldsymbol{\kappa}) = \underbrace{CS(\boldsymbol{p}, \boldsymbol{\tau})}_{\text{consumer surplus}} + \underbrace{\sum_j q_j \mu_j}_{\text{producer surplus}} \underbrace{- \eta \sum_j q_j (\tau_j + \kappa_j)}_{\text{government spending}} - \underbrace{\sum_j q_j \phi_j}_{\text{negative externalities}} \tag{10}$$

Equation (10) takes the perspective of a global planner that internalizes the effects of a policy on all firms and uses a global social cost of carbon. Section 7 considers two alternatives that describe how a domestic planner may evaluate a policy differently than a global planner. The first, W^{US}, takes the view of a total US social planner that places no weight on foreign firms and assumes a domestic social cost of carbon. The second, $\widetilde{W}^{US}$, takes the seemingly contradictory but potentially factual perspective of a domestic social planner that places no weight on foreign production but internalizes the global cost of environmental damages. Labeling ϕ_j^{US} as externalities under an assumed domestic social cost of carbon,

$$W^{US}(\boldsymbol{\tau}, \boldsymbol{\kappa}) = CS(\boldsymbol{p}, \boldsymbol{\tau}) + \underbrace{\sum_{j \in US} q_j \mu_j}_{\text{domestic profits}} - \eta \sum_j q_j (\tau_j + \kappa_j) - \underbrace{\sum_j q_j \phi_j^{US}}_{\text{domestic damages}} \tag{11}$$

$$\widetilde{W}^{US}(\boldsymbol{\tau}, \boldsymbol{\kappa}) = CS(\boldsymbol{p}, \boldsymbol{\tau}) + \underbrace{\sum_{j \in US} q_j \mu_j}_{\text{domestic profits}} - \eta \sum_j q_j (\tau_j + \kappa_j) - \underbrace{\sum_j q_j \phi_j}_{\text{global damages}} \tag{12}$$

We use these three measures to highlight the tradeoffs in green industrial policy between trade and the environment. We separate producer surplus into components from US- versus foreign-owned firms. For calculating these statistics, we define "US producers" as Tesla, Rivian, Lucid, Ford, GM, and the former Chrysler Group brands (Chrysler, Dodge, Jeep, and Ram). We define all others as "foreign producers."[15]

[13] 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 value 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.

[14] Conceptually, we want to compute uninternalized externalities from the vehicle sales which the policy changes we consider do not directly change, over the life of those vehicles in the locations where they are operated. Changes in new vehicle prices induce substitution to used vehicles, taxis, and 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 are currently GVs, we assume that the outside option has the same externality as GVs, except with no manufacturing CO_2 emissions.

[15] 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

In addition to welfare, our counterfactual analyses discuss two other aggregate metrics for policy evaluation: the cost per ton of CO_2 abated and the marginal value of public funds (MVPF, see Hendren and Sprung-Keyser 2020). We define these as

$$\frac{\text{Cost}}{\text{tonCO}_2} = \frac{\Delta CS + \Delta PS - \Delta\text{non-CO2 negative externalities} - \Delta G}{\Delta \text{CO}_2}$$
$$\text{MVPF} = \frac{\Delta CS + \Delta PS - \Delta\text{negative externalities}}{\Delta G}$$

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 interpretive limitations (Hahn et al., 2024). In particular, 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, the MVPF includes only EV tax credit spending in the denominator; we interpret the gas tax as a (fiscal) externality.

Researchers usually interpret the MVPF as an evaluation of government spending. Several of our counterfactuals, however, decrease government spending. The MVPF in these cases may be best thought of as evaluating the higher-spending alternative—e.g., 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

Theory This subsection discusses our methodology for estimating optimal uniform and differentiated EV subsidies, subject to coverage restrictions.[16] 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, i.e. $\mu_j - \phi_j$, as the "price distortion." Below we present results when the MCPF is 1, but Appendix E shows the corresponding derivations with a general MCPF, when financing subsidies generates additional distortions in the economy. We also solve for the optimal consumption subsidy $\boldsymbol{\tau}$ that applies equally to purchases and leases; we do 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 the first-best policy for a global planner (maximizing W) implements a vector of choice-specific Pigouvian subsidies or taxes that offset the price

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.

[16] Holland et al. (2016) solve for the second-best differentiated and uniform EV subsidies, accounting for different emissions rates in the electric grid across space. Building on their work, we incorporate market power distortions, international profit shifting, distortionary taxation, and fatal car accidents.

distortion: $\tau_j^{FB} = \mu_j - \phi_j$.[17] Recall that $\tau_j < 0$ represents a tax. In practice, the IRA and analogous subsidies in other countries may deviate from optimal policy for several reasons. National policymakers may maximize domestic welfare, as in W^{US} or $\widetilde{W}^{US}$. Additionally, institutions or political economy may limit policymakers to applying subsidies to 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 vector of second-best optimal differentiated subsidies $\boldsymbol{\tau}_{\mathcal{S}}^{SB}$ 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 For as the set of foreign-owned firms. Proposition 1 shows that the second-best differentiated subsidies for the US planner do not equal the price distortion alone. Instead, they account for indirect substitution from the set of unsubsidized choices into $\mathcal{S}$ and for the capture of subsidies by foreign-owned firms. (Recall that under the IRA, foreign-owned firms can receive the 30D subsidy if assembly occurs in North America and all firms qualify for the 45W subsidy.) Given the full matrix of demand derivatives $\boldsymbol{\Omega}$, with (j, r)-th element given by $\partial q_r/\partial p_j$, denote the submatrix $\boldsymbol{\Omega}_{\mathcal{S}}$ as the subset of entries corresponding to rows and columns $j, r \in \mathcal{S}$. Correspondingly, denote the submatrix $\boldsymbol{\Omega}_{\backslash\mathcal{S}}$ as the subset of entries with rows $j \in \mathcal{S}$ and columns $r \in \backslash\mathcal{S}$. These submatrices summarize aggregate substitution into $\mathcal{S}$ and away from $\backslash\mathcal{S}$ in response to subsidies.

Proposition 1. *At an MCPF of one, second-best optimal differentiated subsidies for a subset of choices are*

$$\boldsymbol{\tau}_{\mathcal{S}}^{SB} = \underbrace{(\boldsymbol{\mu}_{\mathcal{S}} - \boldsymbol{\phi}_{\mathcal{S}})}_{\textit{price distortion}} + \underbrace{\boldsymbol{\Omega}_{\mathcal{S}}^{-1}\boldsymbol{\Omega}_{\backslash\mathcal{S}}\left(\boldsymbol{\mu}_{\backslash\mathcal{S}} - \boldsymbol{\phi}_{\backslash\mathcal{S}}\right)}_{\textit{indirect substitution}} + \underbrace{\boldsymbol{\Omega}_{\mathcal{S}}^{-1}\boldsymbol{m}_{For}}_{\textit{profit shifting}} \tag{13}$$

Proof. Appendix E.2. □

Here $\boldsymbol{\mu}_{\mathcal{S}} - \boldsymbol{\phi}_{\mathcal{S}}$ represents the vector of price distortions for subsidized choices (in $\mathcal{S}$), $\boldsymbol{\mu}_{\backslash\mathcal{S}} - \boldsymbol{\phi}_{\backslash\mathcal{S}}$ is the vector of price distortions for unsubsidized choices (in $\backslash\mathcal{S}$), and $\boldsymbol{m}_{For}$ is the vector of foreign firm profit changes in response to each subsidy $\tau_j \in \boldsymbol{\tau}_{\mathcal{S}}^{SB}$, e.g. $\sum_{r \in For} \frac{\partial \pi_r}{\partial \tau_j}$. Note that markups, substitution, and profits on the right-hand side in equation (13) are all endogenous to subsidy policy.

Equation (13) has a natural interpretation. At a global social cost of carbon, most EVs, like most vehicles in general, have negative externalities that exceed their markups, implying a first-best tax from the first term in (13). The second term, however, may justify subsidies to EVs if they induce net substitution away from socially costly GVs.[18] The third term in (13) supports taxing

[17] When the MCPF is greater than 1, the global planner equates the cost of the transfer to the government, $\eta \times \tau_j^{FB}$, with the combined distortions in the economy from unpriced externalities and the transfers themselves, $\mu_j - \phi_j - (\eta - 1)q_j$. This last term arises from transfers to inframarginal consumers, each of whom receives a marginal unit of income at a cost of η to taxpayers.

[18] Whether the second term is positive depends the price distortion of each submodel in $\backslash\mathcal{S}$ and the net substitution patterns given by the rows of$\boldsymbol{\Omega}_{\mathcal{S}}^{-1}\boldsymbol{\Omega}_{\backslash\mathcal{S}}$. We cannot say much in general, other than to note that the own-price diagonal

EVs if foreign firms produce many targeted EVs (when $\boldsymbol{m}_{For}$ is generally positive). Alternatively, the third term implies a subsidy if subsidies are directed to US firms (when $\boldsymbol{m}_{For}$ is generally negative).

We also derive the analogous result for the uniform subsidy amount that maximizes US welfare, $\tau^{SB,U}$, which restricts the subsidy amount to be equal for all goods in $\mathcal{S}$. In this setting, demand-response weighted averages provide sufficient information. 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 $\mathcal{S}$ (correspondingly, $\bar{\mu}_{\setminus\mathcal{S}}$ among unsubsidized goods) 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 $\mathcal{S}$.[19]

Proposition 2. *At an MCPF of one, second-best optimal uniform subsidies for a subset of choices are*

$$\tau^{SB,U} = \underbrace{\left(\bar{\mu}_{\mathcal{S}} - \bar{\phi}_{\mathcal{S}}\right)}_{\textit{price distortion}} - \underbrace{\left(\bar{\mu}_{\setminus\mathcal{S}} - \bar{\phi}_{\setminus\mathcal{S}}\right)}_{\textit{indirect substitution}} - \underbrace{\left(\sum_{j\in\mathcal{S}} \frac{dq_j}{d\tau}\right)^{-1}\left(\sum_{j\in For} \frac{d\pi_j}{d\tau}\right)}_{\textit{profit shifting}} \tag{14}$$

Proof. Appendix E.3. □

When only EVs receive a subsidy, the optimal uniform EV subsidy equals the demand response-weighted difference in price distortions between EVs and non-EVs, minus the marginal profit shifted to foreign firms per marginal electric vehicle at the optimal subsidy level. Although equation (14) describes three components, in some cases we aggregate the first two terms so that we report a decomposition into two components—one representing environmental and markup distortions due to encouraging sales of EVs in $\mathcal{S}$ and shifting sales away from vehicles in $\setminus\mathcal{S}$ (the first two terms in the equation); and the other representing a trade incentive to shift profits away from foreign firms. The next section empirically implements a version of this decomposition, which provides further evidence on the importance of environmental and market power distortions versus profit-shifting in guiding EV policy.

We conclude this theory with two additional notes. We implement equations (13) and (14) by treating the equation as a contraction mapping and re-computing markups, profits, and derivatives in each iteration of subsidies. In the more general setting with an MCPF above one, equations (13) and (14) each also has an additional term corresponding to tax distortions.

Descriptive Patterns of Price Distortions We close this section by illustrating the distribution of baseline (negative) price distortions across EVs and GVs in Figure 9, which play important

elements of the substitution matrix $\boldsymbol{\Omega}$ are strictly negative, the cross-price off-diagonal elements are strictly positive, and $\boldsymbol{\Omega}$ is weakly diagonal dominant (when augmented to include the outside option) by unit demand. If the own-price derivative is large in magnitude relative to the cross-price derivatives, each row in $\boldsymbol{\Omega}_{\mathcal{S}}^{-1}\boldsymbol{\Omega}_{\setminus\mathcal{S}}$ will tend to have negative elements and hence the dot product with negative elements in $\left(\boldsymbol{\mu}_{\setminus\mathcal{S}} - \boldsymbol{\phi}_{\setminus\mathcal{S}}\right)$ will sum over positive terms.

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

roles in equations (13) and (14) and will contribute to the constrained optimal subsidies the next section recovers. This graph echoes the histogram of negative externalities in Figure 5, except it uses the model-derived markup to infer social marginal cost.

Figure 9 shows several important properties about the distribution of price distortions. Panel (a) shows that at a global social cost of carbon, 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. Section 7 uses estimated substitution patterns to recover the optimal tax or subsidy in a scenario where policy applies to only some EVs and not GVs. The graph shows substantial dispersion within powertrains, driven by differences across submodels in fuel economy, weight, local pollution, and markups. The magnitude of this dispersion implies that vehicle-specific differentiated taxes or subsidies may generate efficiency gains relative to uniform EV subsidies. The market share-weighted average distortions are about \$6,800 for EVs and \$10,800 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 \$6,400 and \$7,600 respectively. While smaller than the difference between GVs and EVs, the strong within-EV substitution patterns our model estimates means that this difference may be more relevant to our counterfactuals. In particular, it implies that relaxing the 30D trade restrictions will tend to subsidize EVs that are more harmful, i.e., have more negative uninternalized externalities.

Panel (b) of Figure 9 shows the same distributions, but valued at a domestic social cost of carbon. 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 that applies all vehicles is a subsidy to correct for market power distortions, rather than a tax.

7 Effects of Counterfactual Policies

We now use the equilibrium model from Section 6 to evaluate the short- to medium-term impact of the IRA relative to counterfactual policies. Section 7.1 compares the IRA against two types of repeals, eliminating EV credits or reverting to pre-IRA policy, and two trade reforms, a near-removal of the leasing loophole or a lifting of the domestic assembly requirement. Section 7.2 studies constrained optimal EV subsidy policies, with and without requiring uniform EV subsidies across submodels. Our model baseline period describes July and August 2023, which we choose partly since our dealership survey in these months found fairly flexible supply chain conditions.

7.1 Results: Repeal of IRA EV Credits and Modification of Trade Restrictions

Repealing the IRA. Column 1 of Table 5 describes market outcomes observed with the IRA, our baseline, in July and August 2023. Column 2 describes outcomes without any EV tax credits.

Column 3 describes outcomes if policy had continued providing the pre-IRA Section 30D EV credits, under which full \$7,500 purchase and lease credits were available for the first 200,000 EVs each manufacturer sold, and then phased out in the year after the manufacturer reached that limit.[20]

Columns 2 and 3, show that turning of all EV credits or reverting to pre-IRA policy both decrease EV registrations, due to the loss of the tax credits. Rows 4 and 7 show that eliminating EV credits decreases annual EV registrations by 300,000 vehicles and decreases EVs market share from 11 to 8 percent.[21] Column 3 shows that reverting from IRA to pre-IRA policy has impact one-third these magnitudes. Row 8 shows that these counterfactuals decrease leasing by a remarkable 16 percentage points, or just over half relative to baseline leasing rates, because they remove the strong leasing incentive of the IRA's leasing loophole.

These counterfactuals in Table 5, columns 2 and 3, require substantial government spending per additional EV registered. Relative to a scenario with no EV credits, the IRA spends \$23,000 of government revenue per incremental EV registration. Relative to pre-IRA policy with phaseout, the IRA spends \$32,000 per incremental EV registration. Given credit value of \$7,500, these statistics imply that 23 percent to 33 percent of EV credits are additional (\$7,500/\$32,000 or \$7,500/\$23,000), and the rest are inframarginal.

As a benchmark, some environmental policies in other domains have broadly similar additionality rates, though some research laments these values as low. For example, Aspelund and Russo (2024)'s regression discontinuity estimate indicates that 21 to 31 percent of US Conservation Reserve Program contracts for farm conservation are additional. Chen et al. (2024)'s model-based analysis of the market for carbon offsets in China finds that 28 percent of all firms are additional, though 64 percent of registrants are additional.

Several parts of Table 5, columns 2 and 3, show that repealing the IRA credits decreases registrations of vehicles made by US firms but increases registrations of vehicles made by foreign firms. Under a return to pre-IRA policy, foreign EV registrations increase by 67 percent. These repeals decrease the US assembly share of EVs by 10 to 22 percentage points.[22] Again, these large magnitudes occur because the IRA generates a strong preference towards US firms, while pre-IRA credits privileged foreign firms. Table 5 shows that returning to pre-IRA policy has similarly asymmetric effects on foreign versus domestic welfare. Rows 19 through 21 show that reverting to pre-IRA policy decreases US welfare but increases foreign welfare. Despite decreasing the EV market size, this reform still benefits foreign producers by removing domestic preferences in current policy, and therefore improves foreign welfare.

[20] As of July and August 2023, Tesla and GM would have received $\tau = \kappa = 0$, Toyota and Ford would have received $\tau = \kappa = \$7500/4$, BMW and Stellantis would have received $\tau = \kappa = \$7500/2$, and all other firms would have received $\tau = \kappa = \$7500$. By 2024, additional manufacturers would have reached their 200,000 limit, and the pre-IRA Section 30D would have soon implied no tax credits available for any major manufacturer.

[21] "Registrations" sums leases and purchases.

[22] Two reasons may explain the contrast between this finding from our equilibrium model and the somewhat flat North American assembly share of EV in Figure 4, panel (b). As Section 4 discussed, the introduction of new foreign EV submodels in late 2022 might have decreased the North American assembly share of EV submodels in the IRA's absence. Additionally, this contrast may reflect the annual versus short-run demand elasticity difference between monthly time-series data and the equilibrium model.

Breaking up welfare into its components helps explain these welfare effects. Panel (b) of Table 5 shows that repealing the IRA's EV credits decreases US surplus because it harms consumers and harms US producers. This counterfactual has complex effects on externalities. While both types of repeal increase CO_2 emissions, eliminating EV credits decreases US externalities at the domestic SCC but increases them at the global SCC, partly since EVs generate fatal accident externalities. Returning to pre-IRA policy increases US externalities regardless of the SCC. While repealing the credits saves billions in annual government spending, losses in other components of US welfare outweigh this savings, which is why repealing the IRA's EV credits decreases US welfare.

As Section 6.3 discussed, the MVPFs in panel (d) of Table 5 are most easily thought of as reflecting the value of additional government spending in the higher-spending scenario. Relative to a no-credit or a pre-IRA baseline, the IRA credits generate 1 to 2.1 dollars of net value per dollar of spending. Compared to pre-IRA policy, the IRA has a larger MVPF from the perspective of the US than global planner (2 versus 1.3) due to profit shifting.

Overall, the asymmetric effects of an IRA repeal between domestic and foreign outcomes and between trade and the environment illustrate broader challenges in green industrial policy. The IRA decreases both CO_2 emissions and vehicle registrations from foreign firms. Carbon mitigation co-operatively addresses global negative externalities while profit shifting non-cooperatively decreases foreign welfare. This tension explains the conflicted responses from foreign leaders to the IRA discussed in the introduction, who appreciate that the US is seriously addressing climate change but lament that it is doing so via profit shifting. 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 environmental interest groups, who valued its climate change mitigation.

Appendix Tables A4 and A5 show several sensitivity analyses in column 1. We consider a setting with a marginal cost of public funds equal to 1.4, which Finkelstein and Hendren (2020) summarize as a standard benchmark; we consider alternative social cost of carbon equal to \$100 or \$200, and we consider an alternative demand elasticity of -4. 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. Additionally, when we recreate Table 5 under a supply side that satisfies the Nocke-Schutz restrictions that ensure a unique price equilibrium (not shown for space), the results are extremely similar, which suggests our findings are robust to our definition of firms.

Modifying Trade Restrictions. Columns 4 and 5 of Table 5 largely close the leasing loophole by adding trade restrictions for leases or removing them for purchases. These counterfactuals do not completely close the leasing loophole because they leave the IRA's income and MSRP eligibility restrictions on purchases unchanged.

In Table 5, the trade restrictions in column 4 versus the trade relaxation in column 5 generally produce opposite-signed effects on market outcomes. Adding trade restrictions to leases slightly decreases EV registrations, while removing trade restrictions moderately increases EV registrations.

Both counterfactuals decrease the lease share by half relative to the baseline lease rate, since both counterfactuals treat purchases and leases symmetrically. Adding trade restrictions increases the US assembly share, while removing trade restrictions considerably decreases the US assembly share.

Effects of these trade counterfactuals on welfare in Table 5, columns 4 and 5, also shed light on IRA design choices. Both counterfactuals produce opposite-signed impacts on foreign versus US producer surplus, due to profit-shifting. Restricting trade increases CO_2 emissions while liberalizing trade decreases CO_2 emissions. Additional EV registrations do increase domestic negative externalities, due to EVs' greater weight than GVs and the associated fatal accident externality. Rows 25-27 again reveal somewhat different welfare conclusions from the perspectives of different planners. Both columns show the leasing loophole has an MVPF below one from the global planner's perspective.[23] Column 5 is especially interesting—the US planner does not want to remove the trade restrictions, reflected by MVPFs of 0.6 to 0.8, but a global planner might, with a global MVPF of 1.3. This gap between the MVPFs of the domestic and global planners demonstrates why climate policy is challenging—the climate is a global public good, so every country has an incentive to free-ride, and global benefits from CO_2 mitigation greatly exceed domestic benefits.

In summary, this analysis of trade restrictions reveals tradeoffs between trade and the environment, and between foreign and domestic firms. Liberalizing trade makes US consumers better off, 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. This asymmetry also illustrates why these counterfactuals can produce opposite-signed effects on foreign externalities and foreign welfare—they harm foreign countries despite decreasing CO_2 emissions.

7.2 Results: Optimal Policies

Optimal policies. The previous subsection examines specific and potentially realistic reforms to the IRA's EV credits, including repeals. We now turn to consider optimal design of EV credits, subject to specific political economy or other institutional constraints, and following the theoretical description of constrained optimal subsidies in Section 6.4. These counterfactual scenarios have less immediate policy feasibility—for example, we do not imagine that the US government will implement an optimal, submodel-specific subsidy at any foreseeable point. Instead, we investigate these scenarios to learn about general types of EV policy reforms that may increase welfare. We particularly scrutinize tradeoffs between global and national planners' perspectives and benefits of accounting for heterogeneous externalities among EVs.

Of course, this analysis of constrained optimal policies, like our evaluation of reforms to IRA EV credits, depends on our model and its inputs, particularly our externality assumptions. Larger externality reductions from EVs relative to GVs generally make EV subsidies have larger estimated

[23] Because column 4 of Table 5 decreases government spending, the MVPF describes the higher-spending alternative, i.e., it describes the MVPF of the leasing loophole. The column MVPF represents effects of eliminating the loophole by removing trade restrictions for purchases.

benefits, while smaller assumed externality reductions make EV subsidies look worse. Although we use mainstream and leading model assumptions and data inputs, we nonetheless interpret the quantification of optimal policy cautiously, and focus interpretation more on general patterns than exact magnitudes.

Table 6 has similar structure as Table 5. Column 1 shows the IRA baseline. The counterfactual in column 2 preserves the IRA's 30D restrictions on which submodels qualify for subsidies, but replaces the $7,500 IRA subsidy with the uniform subsidy value that maximizes US total surplus. 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. Column 2 describes the optimal choice for a social planner that cares about US welfare, uses the national social cost of carbon, and (for exogenous, perhaps institutional reasons) must set a uniform subsidy with the current 30D vehicle eligibility restrictions. Column 3 lets the planner choose different subsidies for each submodel. Column 4 assumes the planner cares about the global SCC rather than the domestic SCC. We estimate the uniform subsidy in column 2 using equation (14); we estimate the differentiated subsidies in columns 3 and 4 using equation (13). Rows in Table 6 have the same ordering as rows in Table 5, except that the top shows the sales-weighted average subsidy across submodels that was found to be optimal, and panels show the difference relative to a no-EV subsidy baseline.

We choose these counterfactuals for several reasons. Given constraints on the submodels subsidized and differentiation, these scenarios provide some information on the optimality of IRA subsidies in our model. Comparing uniform with differentiated subsidies (columns 2 and 3) clarifies the gains from differentiation. Comparing policy with a domestic versus global SCC (columns 3 and 4) clarifies impacts of global versus national environmental perspective.

Column 2 of Table 6 shows that our estimated US optimal uniform subsidy is $6,355, assuming US policymakers are constrained to choose a uniform subsidy for 30D-eligible submodels. Interestingly, this is only about ten percent below the actual IRA mean credit amount shown in column 1.[24] We do not believe that policymakers in 2022 purposefully chose the actual credit value; they inherited the $7,500 value in nominal terms from policies years earlier and chose to revise qualifying standards but not subsidy magnitude. Relative to the IRA baseline in column 1, this slightly lower subsidy decreases EV registrations by about 75,000 per year and decreases the EV leasing rate by half, since it turns off the leasing loophole. Decreasing the uniform subsidy from the IRA baseline to the column 2 optimum increases US welfare by $1 to 2 billion annually.

Appendix Table A4 revisits this calculation of optimal uniform subsidies under alternative assumptions. Under the global SCC, panel (e) shows a uniform optimal EV subsidy of $9,700, and a mean optimal differentiated subsidy of $14,000. Although Figure 9, panel (a), implies that the optimal policy applied to all vehicles and under the global SCC would be a tax, we find that the 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

[24]The actual mean IRA credit amount, shown in column 1, is slightly below $7500 because some vehicles only qualify for $3,750 in credits.

substitution from GVs to EVs that subsidizing EVs becomes optimal, highlighting the role of the substitution terms of our optimal subsidy formulas in equations (13) and (14). Appendix Table A4 also revisits results using an MCPF of 1.4, reflecting the deadweight loss of taxation. Here the optimal uniform EV subsidy is about \$1,000 with a domestic SCC and \$3,000 with a global SCC, or under a third of what Table 6 finds assuming an MCPF of 1.

Appendix Table A6 applies the decomposition from equation (14) of the constrained optimal uniform subsidies in Table 6. It decomposes these subsidies into four components—price distortions (markups and externalities); indirect substitution; profit shifting; and tax distortion.[25] We find that the profit shifting motive is large, regardless of the SCC and MCPF assumptions. First consider a setting with a global SCC and MCPF of 1, which Table A4 panel (e) shows has an optimal uniform subsidy of \$9,700. This setting provides perhaps the largest scope for environmental benefits relative to non-environmental concerns. Appendix Table A6 shows that here the profit component is about \$3,000, while distortions account for the remaining \$6,700. In this scenario, reducing distortions (market power and externalities) has twice the importance of profit shifting in guiding optimal policy. Alternatively, consider a scenario with a domestic SCC and MCPF of 1.4, which Table A4, panel (a), indicates has optimal uniform subsidy of about \$1,100. This setting gives the least scope for environmental concerns and further adds in the fiscal distortion from taxation. Here Appendix Table A6 shows that the profit shifting component of optimal subsidies is about \$2,600 while the environmental and markup distortions account for \$1,900. However, the tax distortion component is -\$3,400.

What do these results indicate about the weight that US policymakers put on foreign climate benefits? On one hand, the Table 6 finding that the IRA subsidies are somewhat near the optimal value we calculate under a domestic SCC, and well below the optimal value we calculate under a global SCC, might suggest that policymakers effectively used the domestic SCC, and put little weight on foreign climate benefits. This would contrast with the US government's stated policy to use the global SCC (US EPA 2023a) in regulatory design and analysis. On the other hand, the Table A4 finding that under an MCPF of 1.4, the optimal uniform EV subsidy with either the domestic or foreign SCC is far below the IRA's actual value would suggest that other forces besides weight on foreign climate benefits determined the magnitude of these subsidies. Complicating these considerations is the reality that the \$7,500 value was chosen long ago, and the IRA merely left it unchanged. Moreover, our optimal subsidy amounts depend on our externality assumptions. Ultimately, we believe the question of what weight US policymakers put on foreign climate benefits is fascinating and little-studied, but this setting contains insufficient information to conclusively answer it.

Column 2 of Table 6 shows the optimal uniform subsidy, while column 3 shows the optimal differentiated subsidy, so comparing them shows effects of differentiation. The optimal differentiated subsidy spends more for the mean vehicle, at \$8,916, than the optimal uniform subsidy does. This

[25]The tax distortion component exceeds zero only when MCPF>1, so this term does not appear in the main text equations (13) and (14) that assume MCPF=1, but does appear in the appendix formulas (31) and (38) that allow MCPF>1.

happens because the optimal subsidy assigns large amounts to popular vehicles like the Tesla Model 3 and Model Y ($12,000 and $8,300). Other vehicles, like the credit-eligible PHEVs, have subsidies of $4,300 or less. This disparity shifts market share within EVs toward the more-subsidized submodels, increasing the average subsidy amount received. However, subsidy differentiation only slightly increases the EV market share overall, by half a percentage point. At the same time, differentiation increases US producer and consumer surplus and decreases US externalities, but substantially increases government spending. In total, the differentiated subsidy obtains 75 percent greater welfare gain than the uniform subsidy, or equivalently, the uniform subsidy achieves only 57 percent (=1.94/3.43) of the domestic welfare gain of the differentiated subsidy.

Despite this large magnitude, the MVPFs of the uniform and differentiated subsidy have similar values. This comparison illustrates one characteristic of the MVPF—it ranks policies per dollar spent. For comparing policies that have different optimal size, however, a comparison of MVPFs does not provide information on total benefits or differences in scale. Thus, while the uniform and differentiated policy have similar MVPFs, the differentiated policy has far larger net benefits since our calculations indicate that it has larger optimal scale.

Table 6 shows the optimal differentiated subsidy using the US SCC in column 3 and the global SCC in column 4. Comparing them shows consequences of adopting a global environmental perspective. Row 24 shows that optimal policy using the global SCC decreases CO_2 by twice as much as optimal policy using the domestic SCC. In other words, shifting from a national to a global SCC in the policymaker's objective function while maintaining the focus on domestic producer surplus doubles this policy's climate benefits. This reflects an increase in the EV market share from 11 to 13 percent. The US assembly share of EVs also increases from 76 percent under a policy using the national SCC to 83 percent under policy using the global SCC.

Table 6 also shows complex welfare effects due to shifting from a domestic to a global SCC in policy design, seen from comparing columns 3 and 4. US consumer and producer surplus and government spending all roughly double due to using the global SCC, while US negative externalities change much less. These subsidies increase US surplus using the global SCC, though they decrease US surplus using the domestic SCC.

Table 6, Panel (d) describes these reforms' MVPFs. All these MVPFs exceed one, for both the global and US planners, though they are all below 1.5, which puts them in the range of common assumptions about the MCPF. In other words, these reforms may modestly increase welfare, but welfare conclusions ultimately depend on assumptions about the deadweight loss of taxation.

8 Conclusion

The IRA may cost a trillion dollars (Bistline, Mehrotra and Wolfram 2023), making it potentially the most costly climate change investment in human history. We provide the first ex post microeconomic welfare analysis of a central component of this legislation. We study what may be the IRA's most controversial and costly component: 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 also use this setting to investigate more general lessons on policy for electric vehicles with heterogeneous externalities and on tradeoffs between foreign and domestic interests and between trade and the environment in this case study of green industrial policy.

In the IRA's inaugural year, our short-run event study analysis finds little impact on producer transaction prices. Because the IRA had consumers claim these credits on the subsequent year's taxes, this finding implies that consumers received most of the credits' price impact. Event studies also show that the credits substantially increased leasing, in line with trade, income, and price restrictions on eligibility for EV purchases.

To study effects of counterfactual policies, we lay out an equilibrium model of vehicle supply and demand. In the model, the IRA's EV credits have an MVPF of 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 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. We find that the variation in externalities within EVs versus GVs have similar magnitudes, and that failing to price heterogeneous EV externalities misses substantial opportunities for policy to increase welfare.

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., the "Schedule 2" tariffs that would 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 a global public good 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. Green industrial policy accounts for a growing focus with potentially trillions of dollars of investment from the US, EU, China, and other regions.

While economists lament that countries are increasingly using trade restrictions to advance climate change policy, partly led by the IRA, some policymakers celebrate rather than lament 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, through relocating supply chains and encouraging learning-by-doing. In addition, while we study what may be the most costly of the IRA's provisions, political and economic controversy over the IRA's value and impacts make broader analysis of the IRA an important topic 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, 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.

Another question we do not fully explore involves explanation of the tensions in green industrial policy that we highlight. Why do countries design climate policy that benefits foreign countries, but via industrial policy, which non-cooperatively shifts profits? Relatedly, what weight do policy-makers in one country effectively put on environmental benefits abroad? Although a zero weight would reflect non-cooperative policy, regular international negotiations encourage weights above zero (but perhaps not equal to one) on foreign climate benefits. While political economy likely contributes to these decisions, its exact mechanisms are unclear. The role of interest groups likely plays a role—organized lobbies like auto firms benefit from industrial policy and create domestic political pressure for such non-cooperative policy. The structure of benefits may also contribute—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.

Domestic content restrictions and industrial policy are growing as countries both seek politically feasible policies to work around existing trade agreements that focus on tariffs and also seek to expand market share in rapidly-growing green technology markets. While these policies are clearly not first-best, better understanding the cost-effectiveness, efficiency, distributional consequences, political economy, and externalities of these increasingly common second-best policies would be valuable for researchers and policymakers.

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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. Prices are from Cox Automotive. We use nominal prices, without any inflation adjustment.

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 CO_2 (global SCC)	2,719	2,902	1,835	1,813	–
Driving CO_2 (global SCC)	7,273	6,444	11,282	13,833	13,833
Driving local pollutants	2,294	2,256	2,481	378	378
Excess weight in accidents	9,277	9,114	10,069	7,068	7,068
Positive fiscal externality	5,560	5,531	5,703	3,854	3,854
Total negative externality					
Global SCC	16,003	15,185	19,964	19,239	17,425
Domestic SCC	7,162	6,915	8,357	5,393	5,184

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 3: **Parameter Assumptions and Empirical Moments**

Parameter	Source	Target Value	Model Value
Market size (million/year)	U.S. Census Bureau (2024), from Federal Reserve Bank of St. Louis (2024c)	21.9	–
Model-level demand elasticity	Grieco et al. (2023)	-5.36	-5.36
Share of EV buyers whose 2nd choice is EV	NVES	52%	52%
Share of EV buyers whose 2nd choice is an EV in the same vehicle class	NVES	33%	33%
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.

Table 4: **Parameter Estimates**

Parameter	Description	Value
α	Price response parameter	0.661
σ^g	EV-GV nest parameter	0.377
σ^c	Class nest parameter	0.495
σ^m	Submodel nest parameter	0.844

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

Table 5: **Counterfactual Simulation Results**

		(1)	(2)	(3)	(4)	(5)
			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
	Panel (a): Market Aggregates under Counterfactual Scenario					
1.	Vehicle registrations (000s/year)	10,580	10,406	10,530	10,547	10,671
2.	US firms (000s/year)	3,965	3,704	3,656	3,972	3,922
3.	Foreign firms (000s/year)	6,615	6,702	6,875	6,576	6,749
4.	EV registrations (000s/year)	1,184	867	1,095	1,123	1,351
5.	US firms (000s/year)	835	525	509	832	815
6.	Foreign firms (000s/year)	349	342	586	291	536
7.	EV market share (%)	11.2	8.33	10.4	10.6	12.7
8.	Lease share, within EVs (%)	29.3	12.2	13.0	13.2	14.4
9.	US assembly share, within EVs (%)	70.5	59.9	48.5	74.3	59.7
	Panel (b): Surplus Effects Relative to IRA Baseline ($billion/year)					
10.	ΔUS consumer surplus	-	-5.07	-1.47	-0.97	2.65
11.	ΔGlobal producer surplus	-	-2.12	-1.32	-0.06	0.37
12.	ΔUS producer surplus	-	-2.94	-3.71	0.26	-0.84
13.	ΔForeign producer surplus	-	0.81	2.40	-0.32	1.21
14.	ΔGlobal neg. externalities (global SCC)	-	0.87	0.86	-0.06	-0.29
15.	ΔUS neg. externalities (domestic SCC)	-	-0.52	0.14	-0.18	0.30
16.	ΔForeign neg. externalities (foreign SCC)	-	1.39	0.73	0.12	-0.59
17.	ΔUS government spending	-	-7.38	-2.84	-1.57	2.48
18.	ΔGlobal surplus	-	-0.69	-0.81	0.60	0.83
19.	ΔUS total surplus (global SCC)	-	-1.50	-3.21	0.92	-0.38
20.	ΔUS total surplus (domestic SCC)		-0.11	-2.48	1.04	-0.97
21.	ΔForeign total surplus (foreign SCC)		-0.57	1.67	-0.44	1.80
	Panel (c): Impacts on CO_2					
22.	ΔCO_2 emissions (million tons/year)		6.51	3.41	0.58	-2.77
23.	Global cost/ton CO_2 abated ($/ton)	-	135	4.28	1,271	-58.9
24.	US cost/ton CO_2 abated ($/ton)	-	10.1	-698	1,824	376
	Panel (d): MVPF of Higher-Spending versus Lower-Spending Scenario					
25.	Global MVPF	-	1.09	1.28	0.62	1.33
26.	US MVPF (global SCC)	-	1.20	2.13	0.42	0.85
27.	US MVPF (domestic SCC)	-	1.02	1.87	0.34	0.61
28.	Cost per additional EV ($000s/EV)		23.2	32.0	25.7	14.9

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 mostly close the "leasing loophole" by adding the Section 30D trade restrictions to all leases, although the buyer income restrictions and MSRP caps 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. New vehicle registrations include only leases and purchases by individuals, not vehicles sold to organizations. 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."Foreign SCC" is global SCC minus US SCC. 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.

Table 6: **Counterfactual Simulation Results: Optimal Subsidies**

		(1) IRA	(2) US-optimal uniform EV subsidy with 30D restrictions	(3) US-optimal differentiated EV subsidy with 30D restrictions	(4) US-optimal differentiated EV subsidy with 30D restrictions, global SCC
	Panel (a): Market Aggregates under Counterfactual Scenario				
1.	Mean EV subsidy in this counterfactual	\$7,180	\$6,355	\$8,916	\$14,331
2.	(Standard deviation)	(1,048)	(0)	(3,362)	(4,260)
3.	Vehicle registrations (000s/year)	10,580	10,540	10,574	10,721
4.	US firms	3,965	3,964	4,053	4,322
5.	Foreign firms	6,615	6,577	6,521	6,399
6.	EV registrations (000s/year)	1,184	1,111	1,172	1,438
7.	US firms	835	823	921	1,230
8.	Foreign firms	349	288	251	208
9.	EV market share (%)	11.2	10.5	11.1	13.4
10.	Lease share, within EVs (%)	29.3	13.6	11.5	10.9
11.	US assembly share, within EVs (%)	70.5	72.6	75.3	82.6
	Panel (b): Surplus Effects Relative to No EV Subsidy Baseline (\$billion/year)				
12.	ΔUS consumer surplus	5.07	3.90	4.88	9.21
13.	ΔGlobal producer surplus	2.12	1.70	3.06	6.25
14.	ΔUS producer surplus	2.94	2.82	4.64	8.88
15.	ΔForeign producer surplus	-0.81	-1.12	-1.58	-2.63
16.	ΔGlobal neg. externalities (global SCC)	-0.87	-0.45	-1.95	-3.59
17.	ΔUS neg. externalities (domestic SCC)	0.52	0.52	-0.23	-0.26
18.	ΔForeign neg. externalities (foreign SCC)	-1.39	-0.98	-1.72	-3.33
19.	ΔUS government spending	7.38	5.23	8.04	17.5
20.	ΔGlobal surplus	0.69	0.82	1.84	1.52
21.	ΔUS total surplus (global SCC)	1.50	1.94	3.43	4.15
22.	ΔUS total surplus (domestic SCC)	0.11	0.97	1.71	0.82
23.	ΔForeign total surplus (foreign SCC)	0.57	-0.14	0.13	0.69
	Panel (c): Impacts on CO_2				
24.	ΔCO_2 emissions (million tons/year)	-6.51	-4.59	-8.06	-15.6
25.	Global cost/ton CO_2 abated (\$/ton)	135	62.0	11.8	144
26.	US cost/ton CO_2 abated (\$/ton)	10.1	-183	-185	-25.0
	Panel (d): MVPF versus No EV Subsidy				
27.	Global MVPF	1.09	1.16	1.23	1.09
28.	US MVPF (global SCC)	1.20	1.37	1.43	1.24
29.	US MVPF (domestic SCC)	1.02	1.18	1.21	1.05
30.	Cost per additional EV (\$000s/EV)	23.2	21.4	26.4	30.7

Notes: This table presents counterfactual simulation results for the IRA and alternative policies, relative to a common baseline of no EV subsidies (Coleman 2 in Table 5). 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 simulate the choice-specific differentiated EV subsidy that maximizes US total surplus with the domestic SCC. In column 4, we simulate the choice-specific deifferentiated EV subsidy that maxiumizes US total surplus with the global 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 that are eligible to receive the credits under Section 30D. 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 addditional EV is the ratio of Δgovernment spending to Δnew EVs registered.

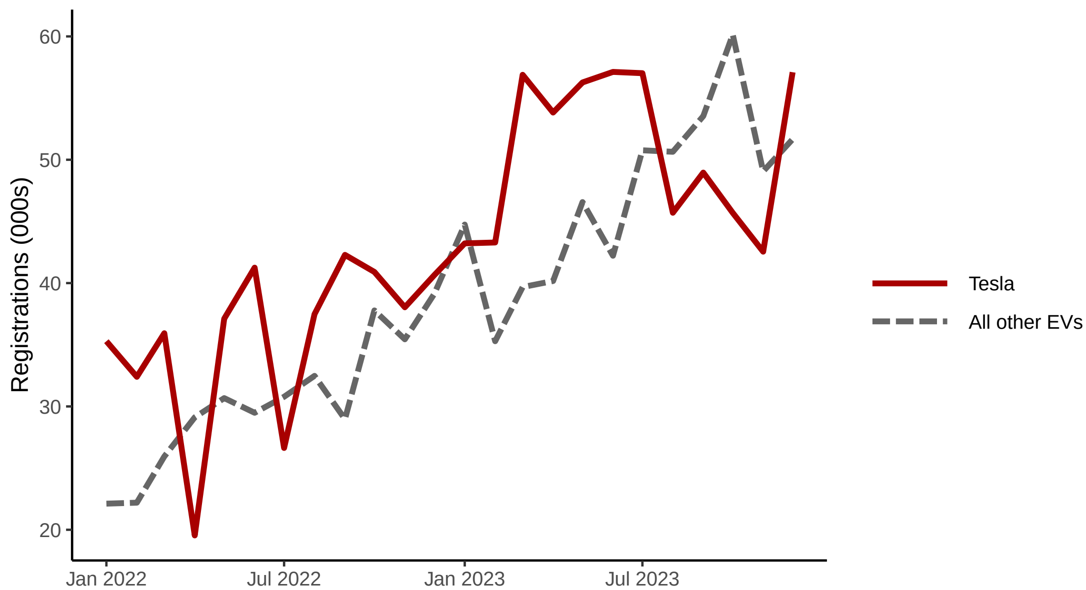
Figure 1: **Section 30D Purchase Credit Eligibility**

<table>
<tr><th>Eligibility group</th><th>Models</th><th>Pre-IRA</th><th>8/17/22 - 12/31/22</th><th>1/1/23 - 4/17/23</th><th>4/18/23 - Late 2023</th></tr>
<tr><td></td><td></td><td>Exclude if sales > 200k</td><td>Exclude if assembled outside North America</td><td>Re-include if sales > 200k; exclude if MSRP > $55k/$80k</td><td>Exclude foreign battery minerals/components</td></tr>
<tr><td>Excluded Aug 2022</td><td>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)</td><td>$7,500</td><td></td><td></td><td></td></tr>
<tr><td></td><td>BMW (530e PHEV); Kia (Sorento PHEV, Sportage PHEV); Toyota (Prius PHEV)</td><td>$3,750 - $7,500</td><td></td><td></td><td></td></tr>
<tr><td>Included Jan 2023</td><td>Chevrolet (Bolt, Bolt EUV); Tesla (Model 3, Model Y)</td><td></td><td></td><td colspan="2">$7,500</td></tr>
<tr><td>Excluded/reduced Apr 2023</td><td>Ford (E-Transit, Mustang Mach-E); Jeep (Grand Cherokee PHEV, Wrangler PHEV); Rivian (R1S, R1T)</td><td colspan="3">$7,500</td><td>$3,750</td></tr>
<tr><td></td><td>Ford (Escape PHEV)</td><td colspan="3">$3,750 - $7,500</td><td>$3,750</td></tr>
<tr><td></td><td>Audi (Q5 PHEV); BMW (X5 PHEV); Nissan (Leaf)</td><td colspan="3">$7,500</td><td></td></tr>
<tr><td>Excluded Jan 2023</td><td>Lucid (Air); Mercedes-Benz (EQS)</td><td colspan="2">$7,500</td><td></td><td></td></tr>
<tr><td>Always included</td><td>Chrysler (Pacifica PHEV); Ford (F-150 Lightning); Volkswagen (ID.4)</td><td colspan="4">$7,500</td></tr>
<tr><td>Always excluded</td><td>Tesla (Model S, Model X)</td><td></td><td></td><td></td><td></td></tr>
</table>

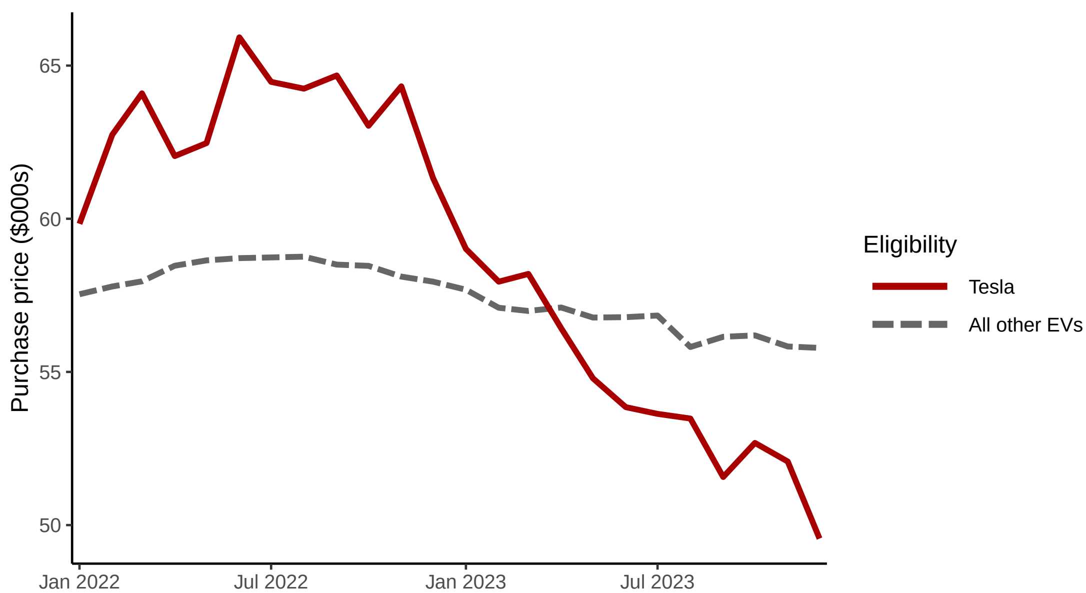
Notes: This figure shows which models are eligible for the IRA Section 30D purchase credit by time period. The figure includes models averaging more than 300 sales per month in 2022 and 2023. The shading intensity indicates the credit amount that the model is eligible for. The red, blue, and orange colors 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: **Monthly Registrations and Prices of Teslas and Other EVs**

(a) **Registrations**



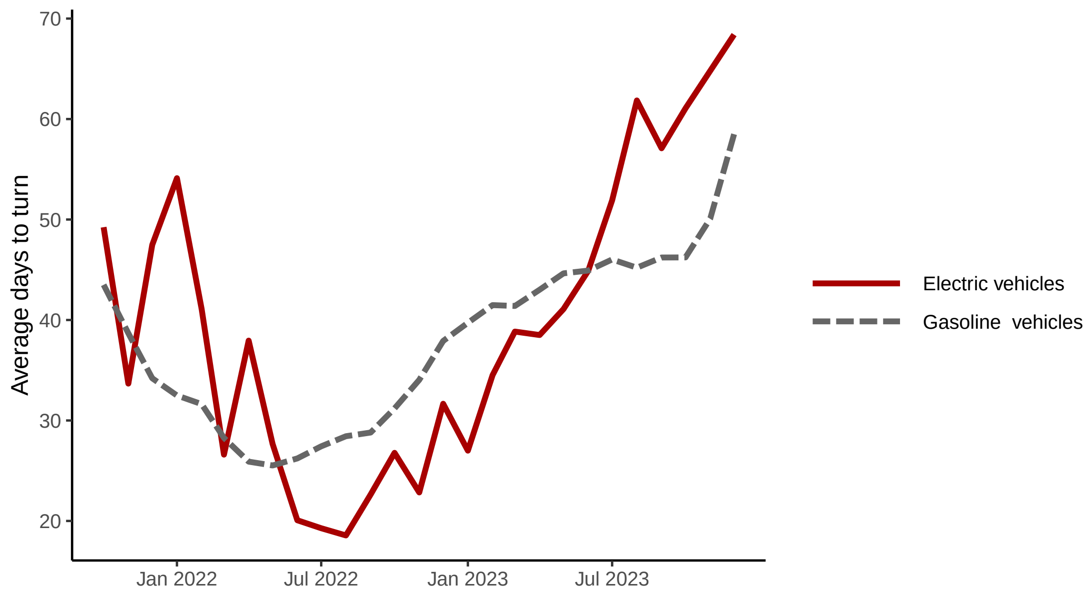
(b) **Average Purchase Prices**



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 3: **Electric Vehicle Supply Constraints**

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



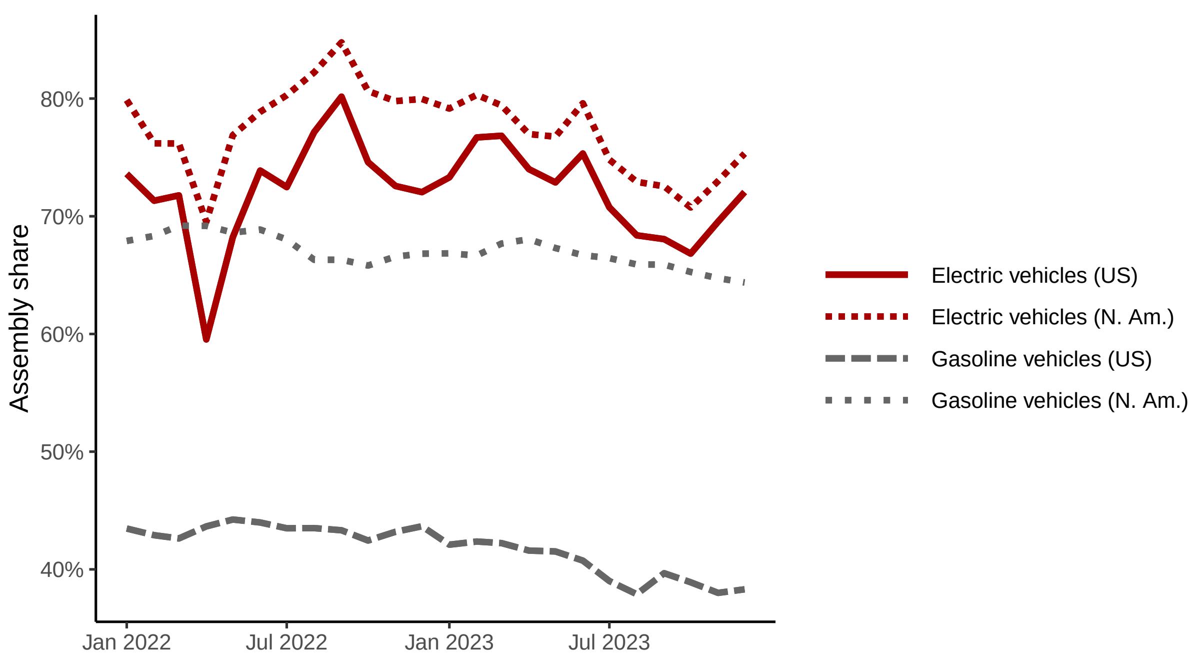
(b) **Tesla Estimated Wait Times**

Notes: Panel (a) presents 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 average delivery wait time reported on the Tesla website (Tesla 2023; Tom 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 4: **Aggregate Electric Vehicle Market Trends**

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

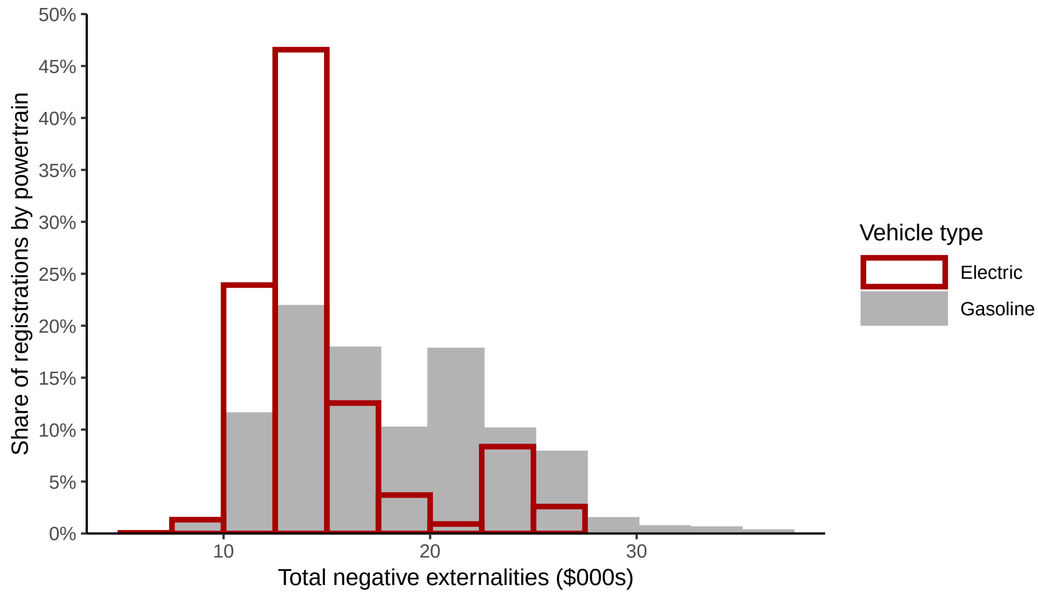
(b) **Share of New Electric Vehicle Registrations that Are Assembled in the US**



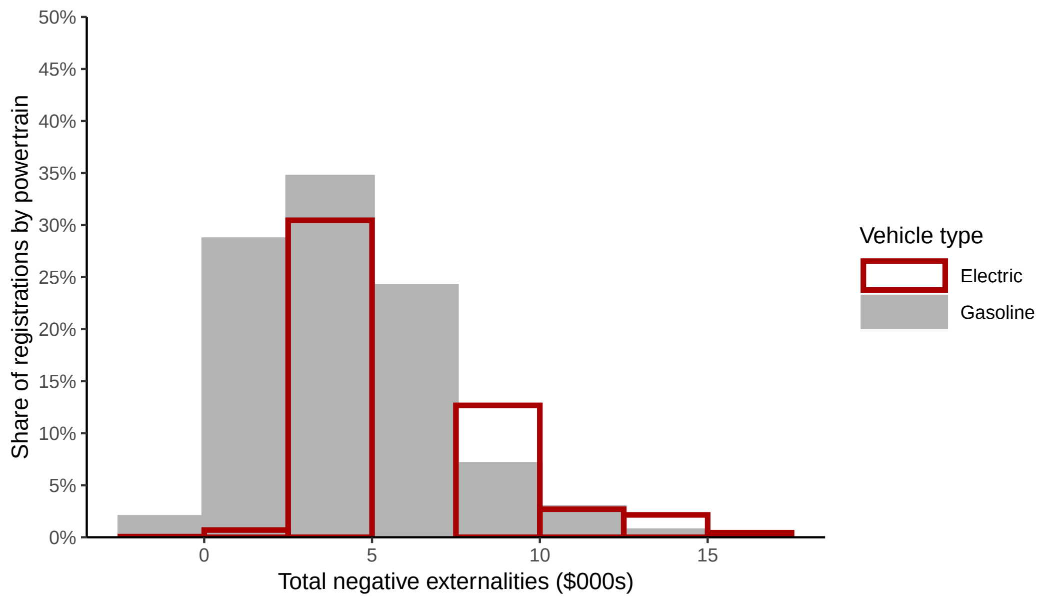
Notes: Panel (a) presents the share of new vehicle registrations that are EVs. Panel (b) presents the share of new vehicles registered that are assembled in the United States.

Figure 5: **Distribution of Negative Externalities Across Submodels**

(a) **Global SCC**



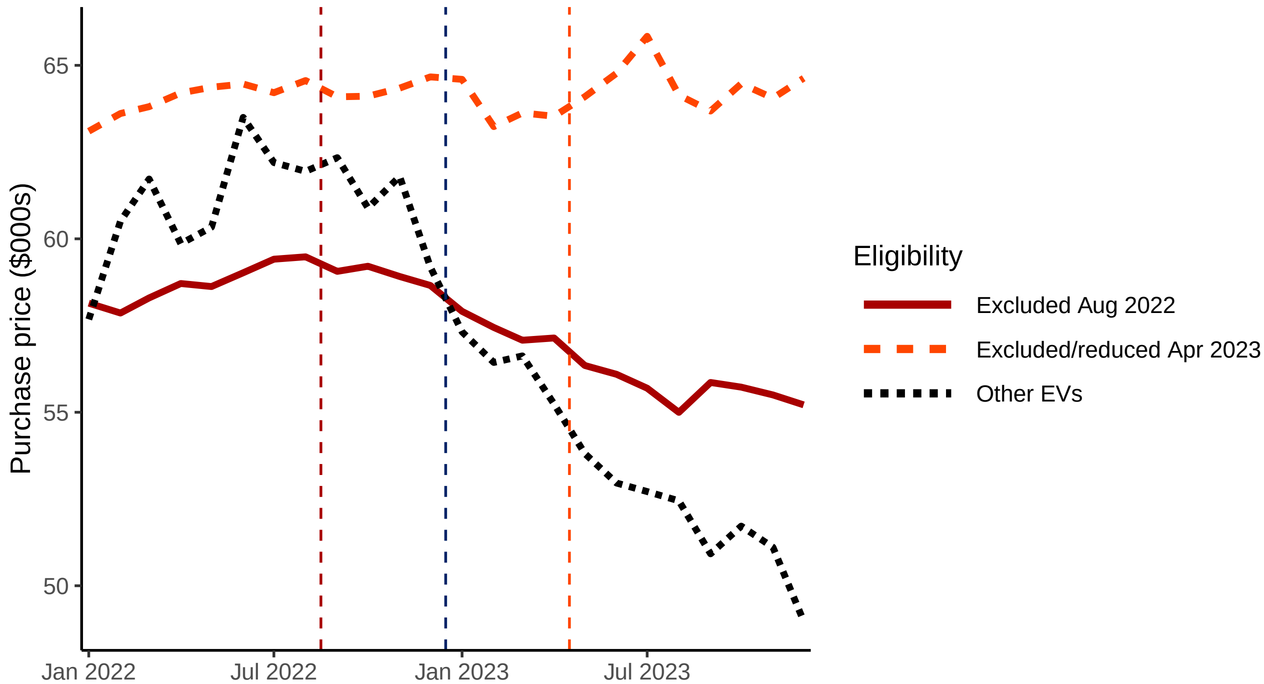
(b) **Domestic SCC**



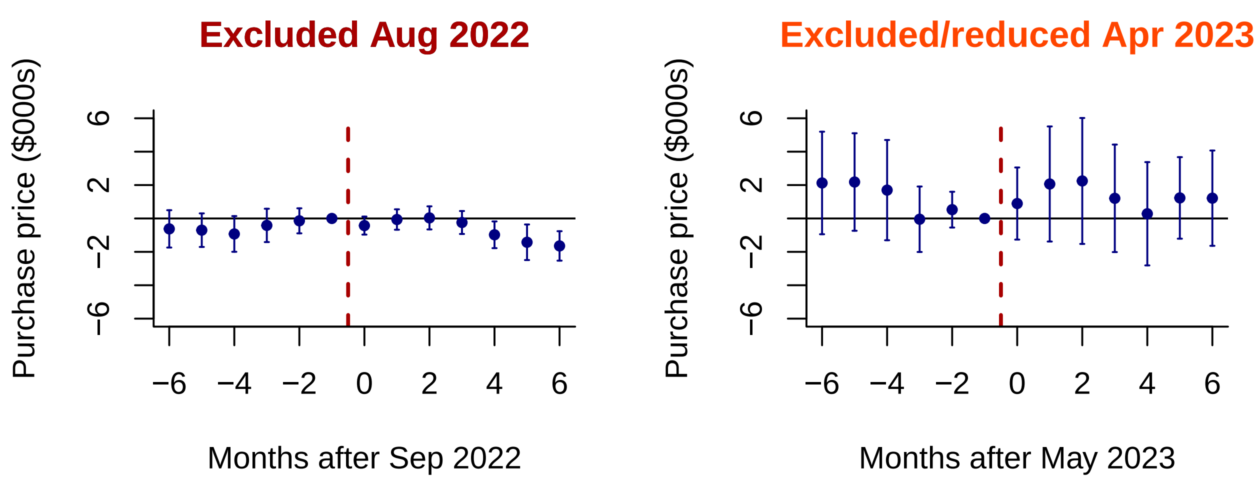
Notes: This figure shows the distribution of total negative externalities across submodels, weighting submodels by registrations in July and August 2023. Carbon damages are evaluated at the global SCC of $241 in panel (a), and at the domestic SCC of $28 in panel (b).

Figure 6: **Purchase Price Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



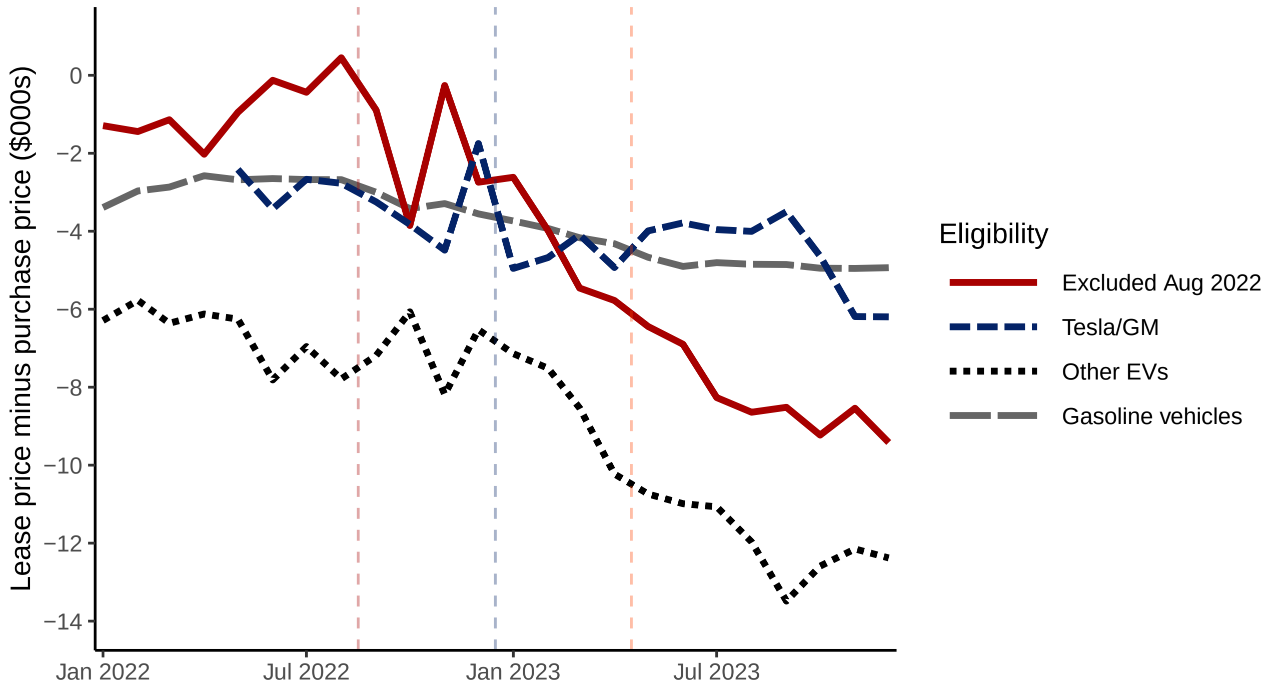
(b) **Event Study Estimates**



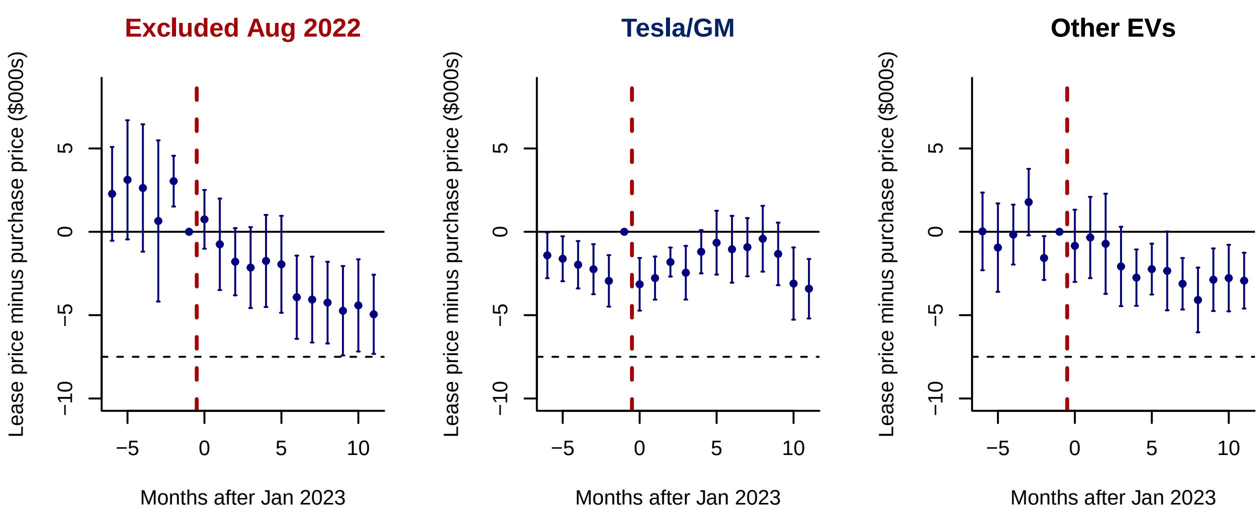
Notes: Panel (a) presents purchase price indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). 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 7: **Relative Lease Price Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



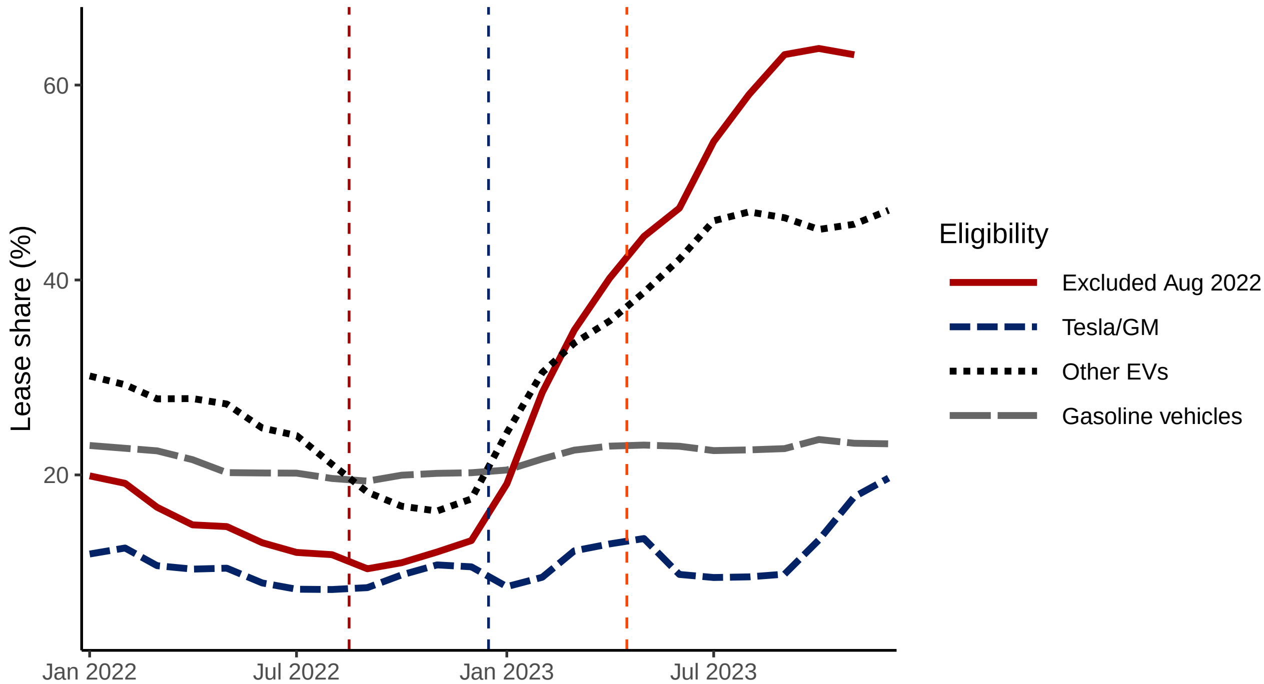
(b) **Event Study Estimates**



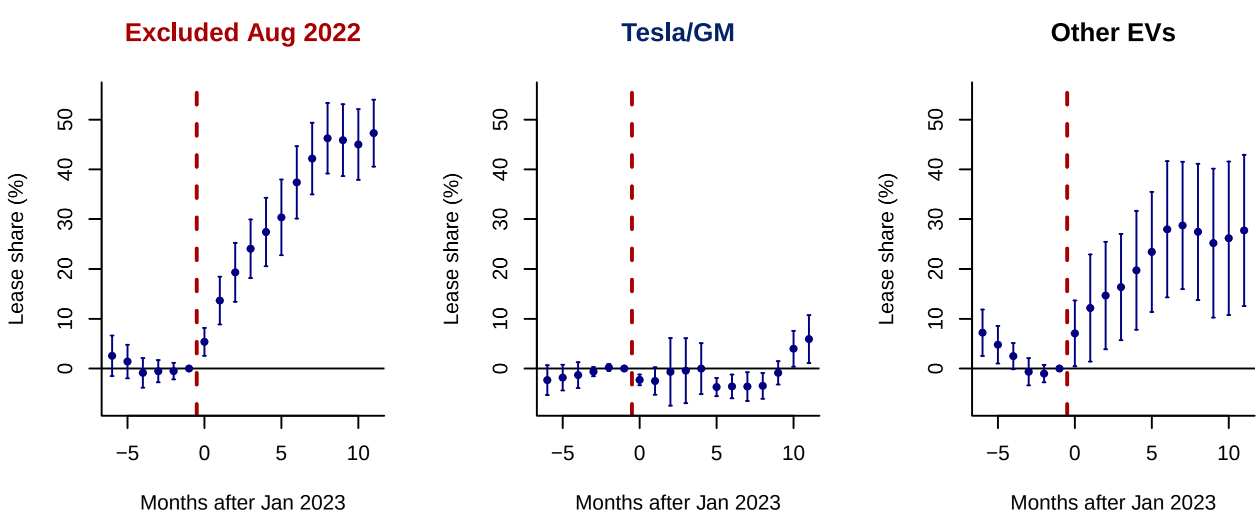
Notes: Panel (a) presents lease price minus purchase price indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). 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 8: **Lease Share Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



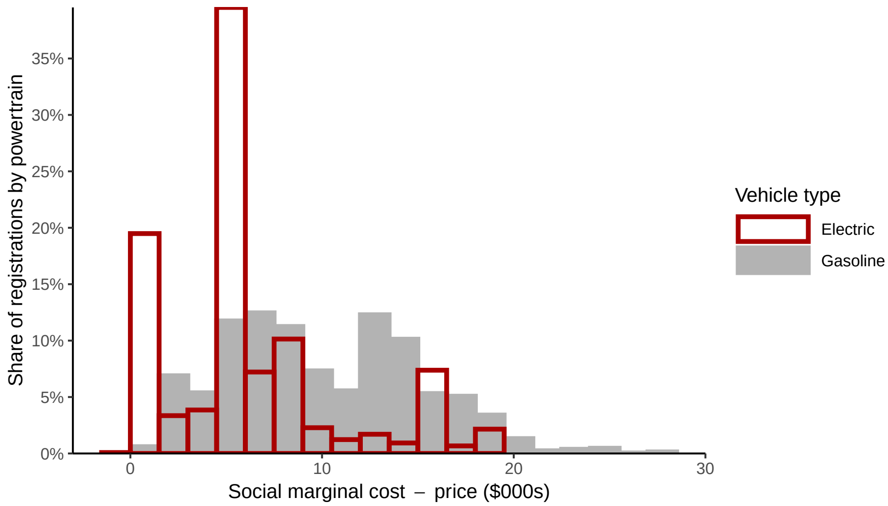
(b) **Event Study Estimates**



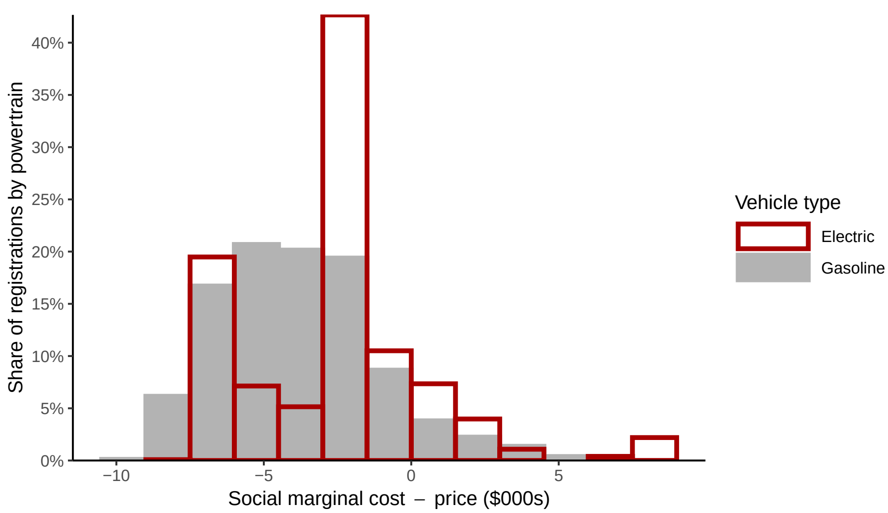
Notes: Panel (a) presents lease share indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). 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 9: **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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Table of Contents

A Data Appendix

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. Because the Cox data also include purchase transactions, we are able to obtain submodel$\times$month-level purchase prices which, combined with lease terms, allow us to compute lease prices. 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).

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.[26] For vehicles with odometer readings that 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

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

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.

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$\times$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 Cox, 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.2) 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.

A.1 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 the regional short-run marginal emission rates from Holland et al. (2016).[27] To aggregate across geographies to the national level, we average across zip codes 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.

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), and we again compute the weighted average marginal damage across zip codes using marginal damage estimates for local pollutants from Holland et al. (2016). We assume that 63 percent of PHEV miles traveled are on gasoline and 37 percent are on electricity, following Plötz et al. (2020).

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). We follow the Anderson and Auffhammer (2014) assumptions for the first two parameters.

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 64 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.

[27]Since new vehicles sold in 2023 will likely be on the road for over a decade, we could also consider estimates of long-run marginal emission rates; this would increase the externality reduction benefit from EVs. Holland et al. (2022) show that short-run marginal emission rates increased slightly from 2010–2019.

A.2 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

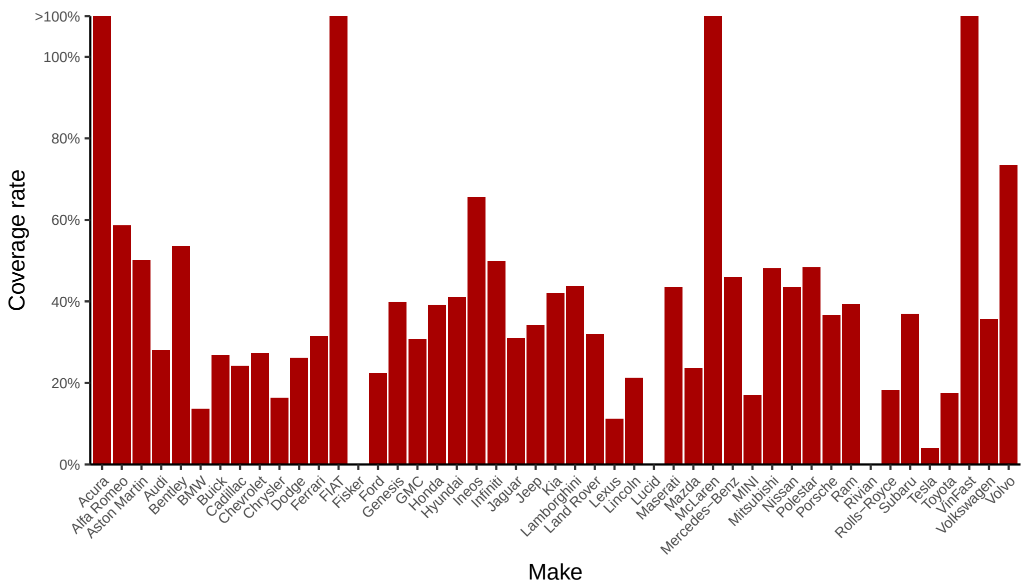
> Hello, my name is ____ and I'm interested in purchasing a [*model name*]. I would be paying cash for the vehicle. When would be a feasible delivery time for the vehicle? How much should I expect to pay? How about delivery times for your other electric or plug-in hybrid vehicles?

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 681 dealership-model combinations.

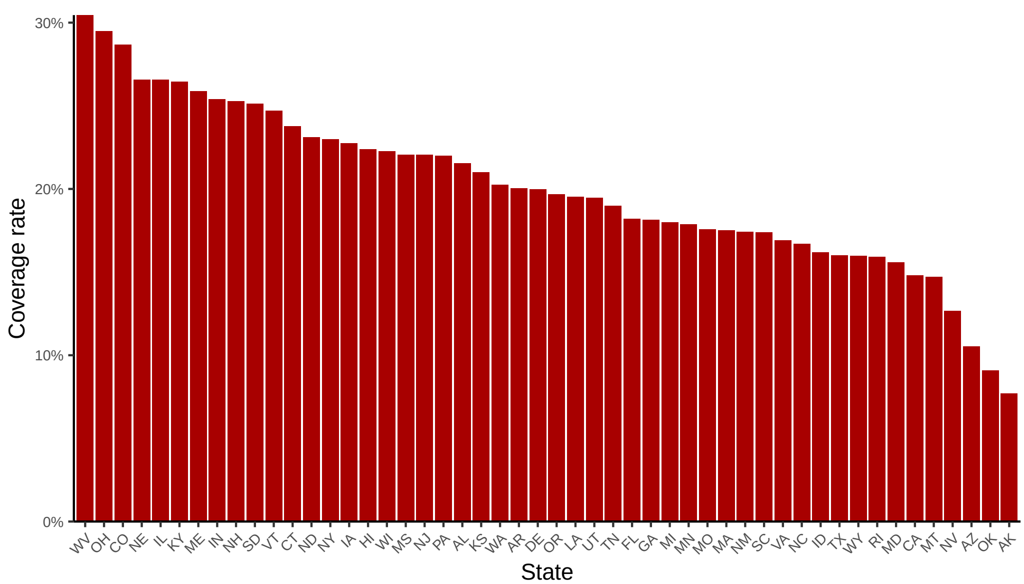
For each dealership-model combination with non-zero wait time, we assign the midpoint of the predicted window given as that dealership-model wait time. We then take the minimum of these across cities to obtain a city-model dataset. These data are merged with EV-Volumes registration records from July 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.

Figure A1: **Cox Data Coverage Rate**

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

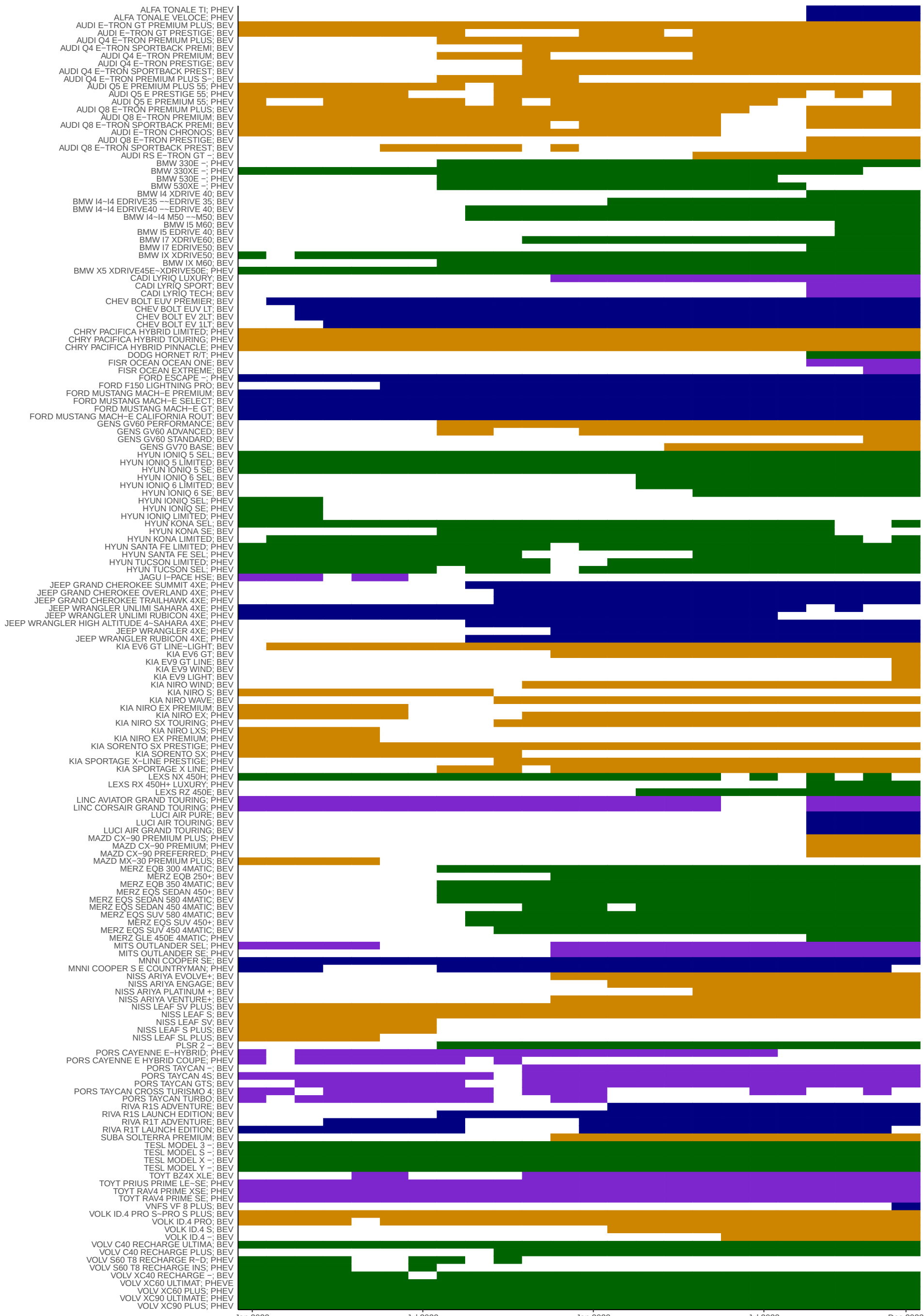


(b) **Cox Data Coverage Rate by State**



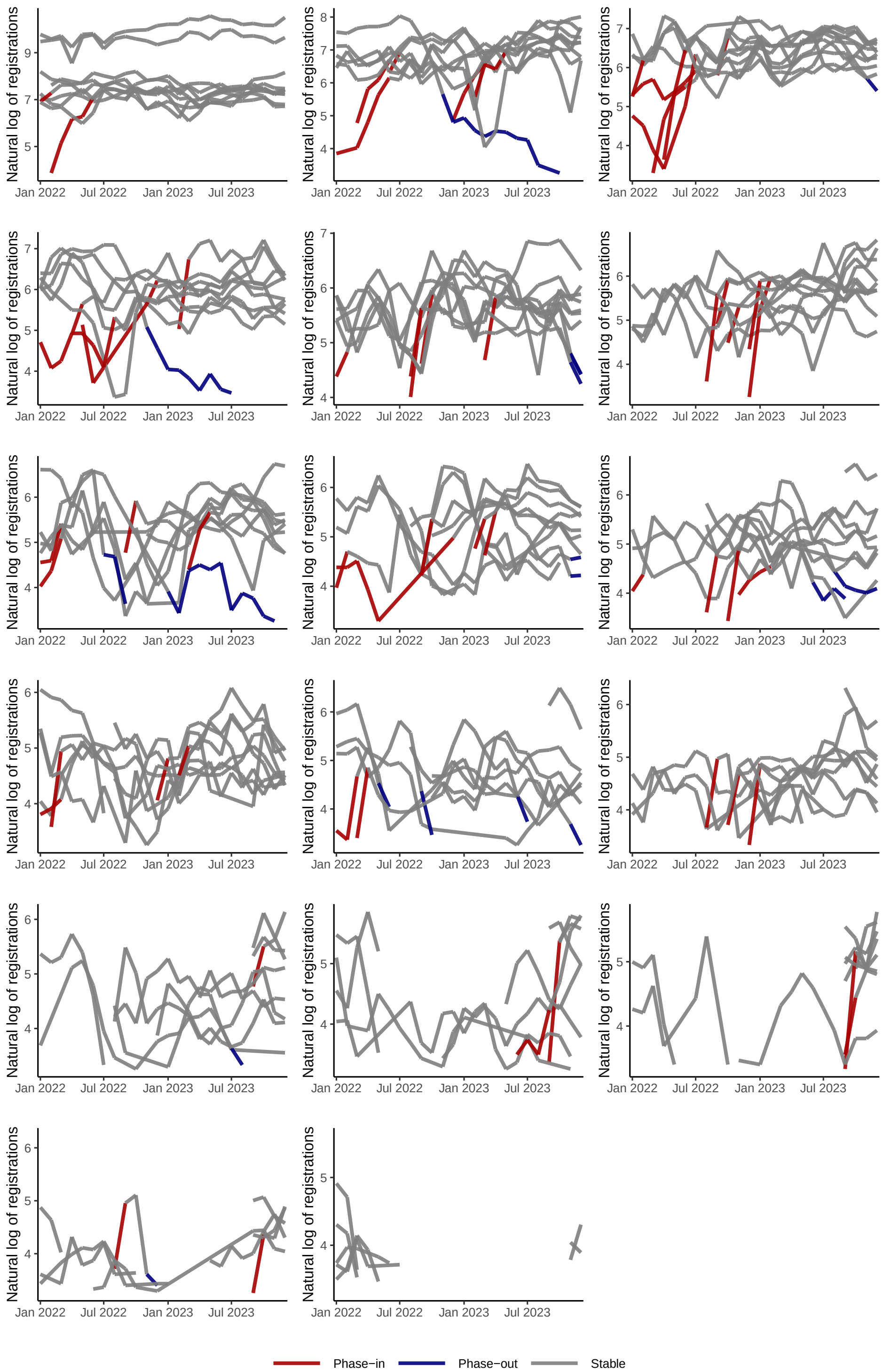
Notes: Panel (a) shows the ratio of new vehicle transactions in the Cox dealership data to nationwide new vehicle registrations in the Experian data, for each make. Panel (b) shows the ratio of new vehicle transactions in the Cox dealership data to state-level registrations from 2023.

Figure A2: **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.

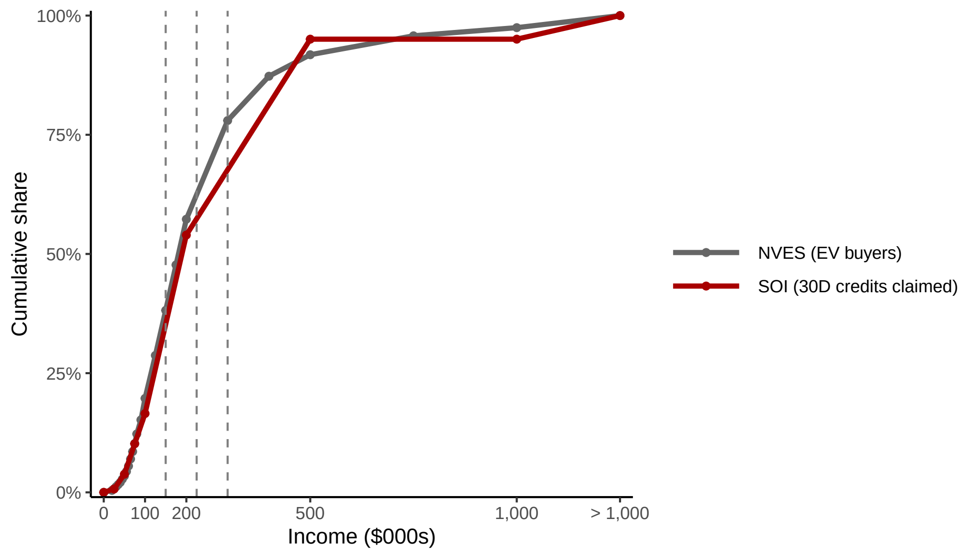
Figure A3: **Phase-In and Phase-Out Periods by Submodel**



Notes: This figure presents registrations by submodel, with one line for each EV submodel in our data. 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 $\bar{q}_j/2$.

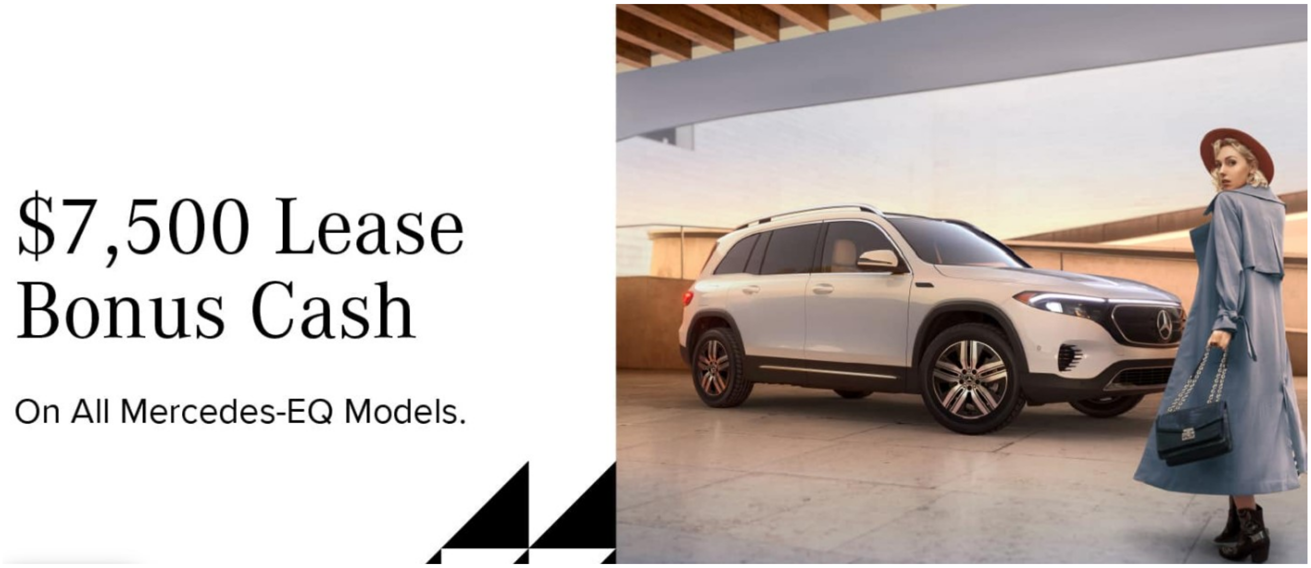
B Descriptive Facts Appendix

Figure A4: **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 A5: **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.

Table A1: **Variation in Externalities by Powertrain**

	Standard deviation ($000s)		Coefficient of variation		Interdecile ratio	
	EVs	GVs	EVs	GVs	EVs	GVs
Panel (a): Global SCC						
Total negative externalities	4.24	5.05	0.25	0.25	1.08	1.07
	[0.031]		[0.946]		[−0.02, 0.01]	
Carbon damages	2.13	3.05	0.20	0.19	1.05	1.05
	[0.000]		[0.600]		[−0.01, 0.01]	
SMC minus price	4.24	5.05	0.25	0.25	1.08	1.07
	[0.031]		[0.947]		[−0.02, 0.01]	
Panel (b): Domestic SCC						
Total negative externalities	2.92	2.98	0.39	0.50	1.11	1.17
	[0.830]		[0.014]		[−0.09, −0.03]	
Carbon damages	0.25	0.35	0.20	0.19	1.07	1.06
	[0.000]		[0.600]		[−0.01, 0.02]	
SMC minus price	2.92	2.98	0.39	0.50	1.11	1.17
	[0.830]		[0.014]		[−0.09, −0.03]	

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. Bracketed values in the *Coefficient of variation* column are p-values for the difference in coefficients of variation, computed following Feltz and Miller (1996); bracketed values in the *Interdecile ratio* column are bootstrapped 95% confidence intervals for the difference in interdecile ratio.

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). Combining these two sources, we computed the early buyout rate in Texas by a) filtering to vehicles which were recorded as leased in the Cox data, and b) identifying vehicles who were re-registered to a different address within three months of their initial registration. The overall 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, while in early 2023 EVs had an early buyout rate of around 1.4%. 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 of 2022 and April of 2023.

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

Clustered (model) standard-errors in parentheses

Notes: This table presents regression results for the group of EVs which were excluded from 30D eligibility in August of 2022. It compares outcomes for July-August of 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.

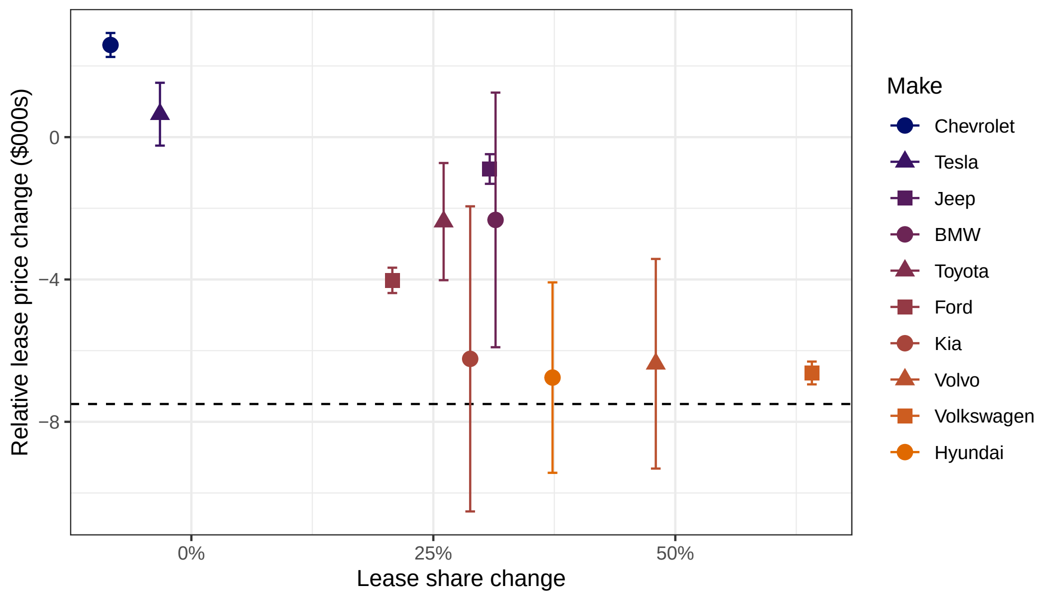
Table A3: **Estimated Purchase Price Effects**

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

Clustered (model) standard-errors in parentheses

Notes: This table presents regression results for the group of EVs which were excluded from 30D eligibility in August of 2022 and in either excluded from 30D or who experienced reductions in purchase credits in April of 2023. The pre-period is defined as the three months prior to the eligibility change (considered to be September of 2022 and May of 2023, respecrtively); 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.

Figure A6: **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.

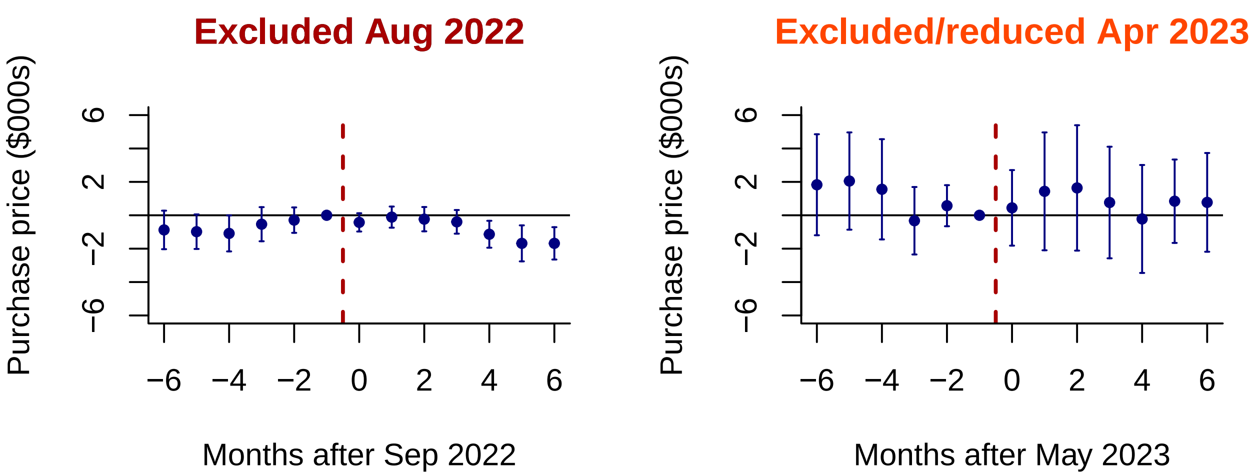
C.2 Doubly-Robust Event Studies

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.

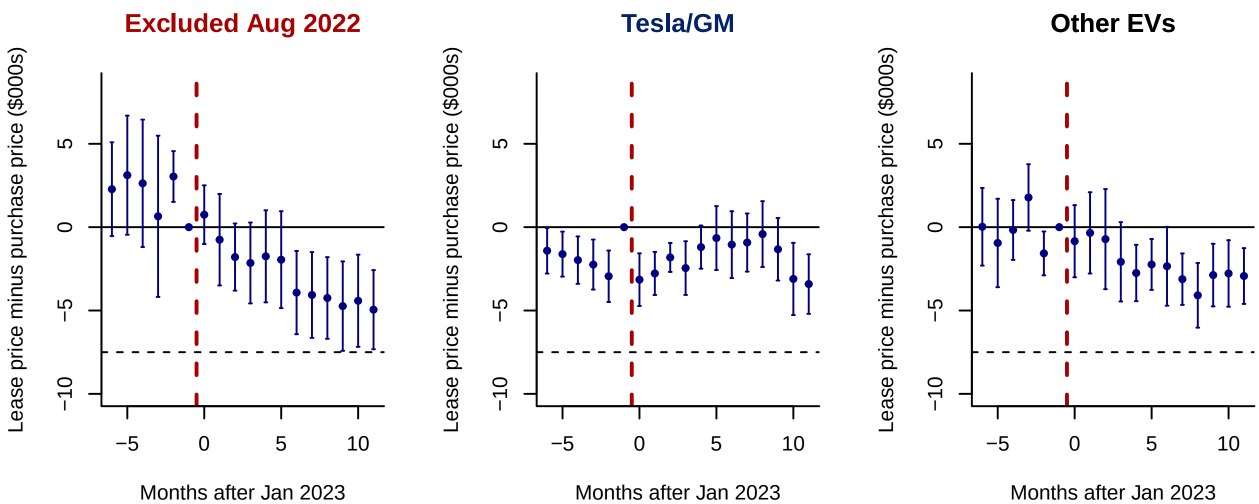
Appendix Figures A7–A9 present the reweighted event study estimates.

Figure A7: **Purchase Price Event Study with Reweighted Controls**



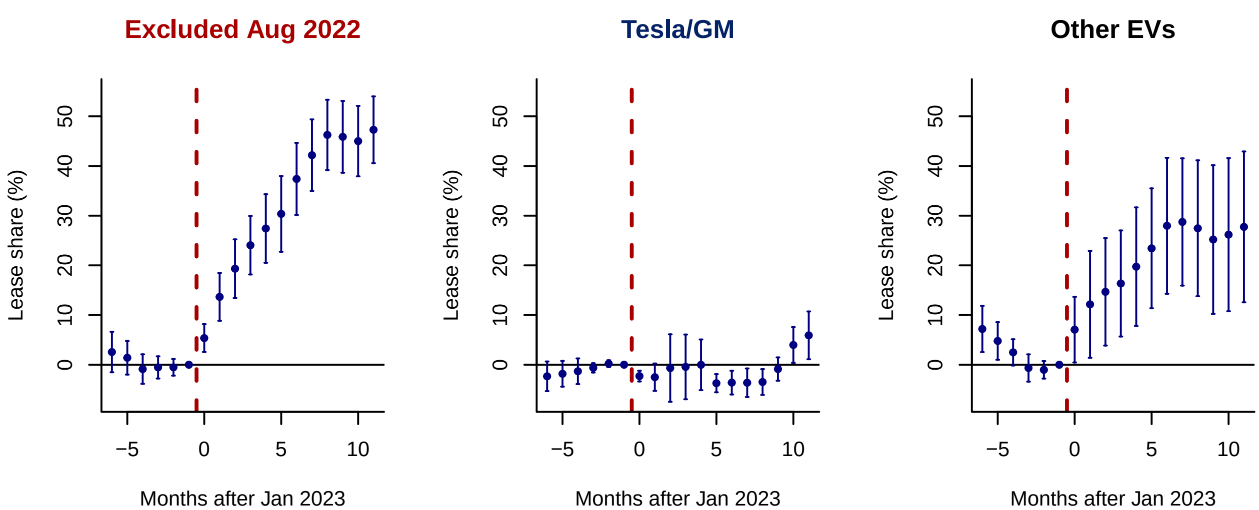
Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). Eligibility groups are described in Figure 1. This parallels Figure 6, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

Figure A8: **Lease Price Event Study with Reweighted Controls**



Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). Eligibility groups are described in Figure 1. This parallels Figure 7, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

Figure A9: **Lease Share Event Study with Reweighted Controls**



Notes: This figure presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). Eligibility groups are described in Figure 1. This parallels Figure 8, except that we also re-weight the control observations (GVs) to match the average pre-IRA EV price.

C.3 Event Studies with Registration Quantities

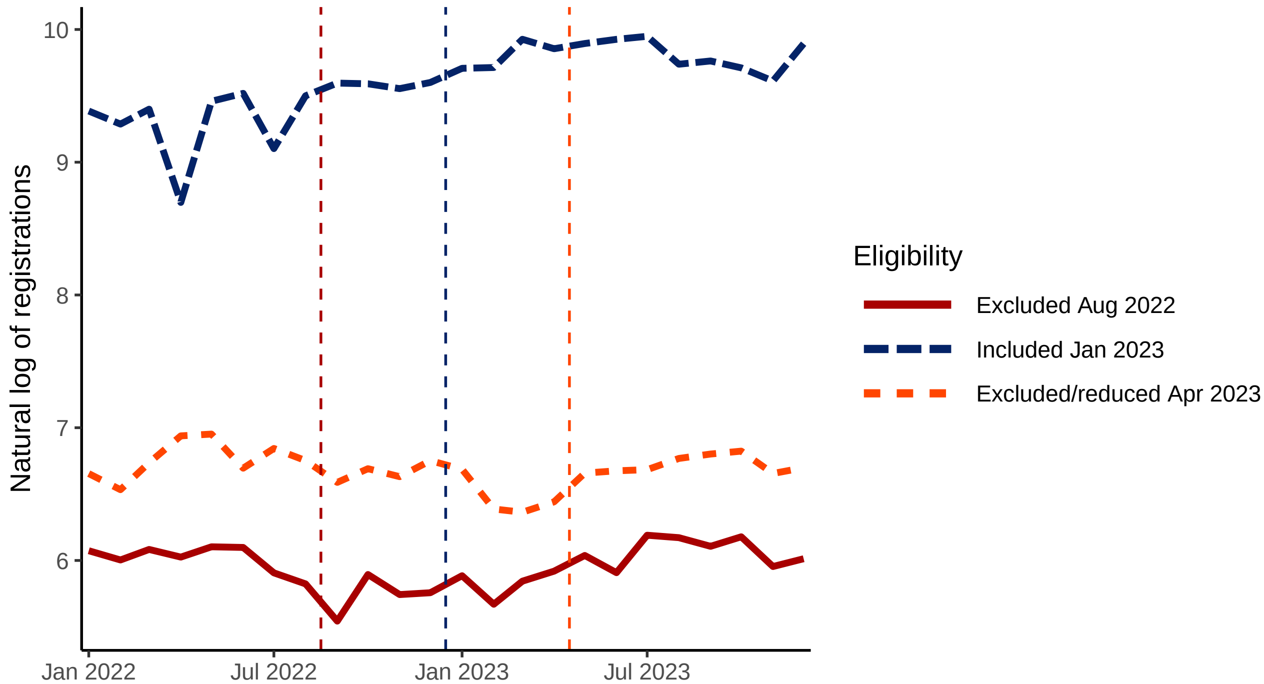
This appendix presents event studies of changes in total registrations (including both purchases and leases) around the 30D vehicle eligibility changes. The IRA should affect total registrations in several ways. First, changes in vehicle eligibility for Section 30D credits should shift demand among income-eligible 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.

Appendix Figure A10 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).

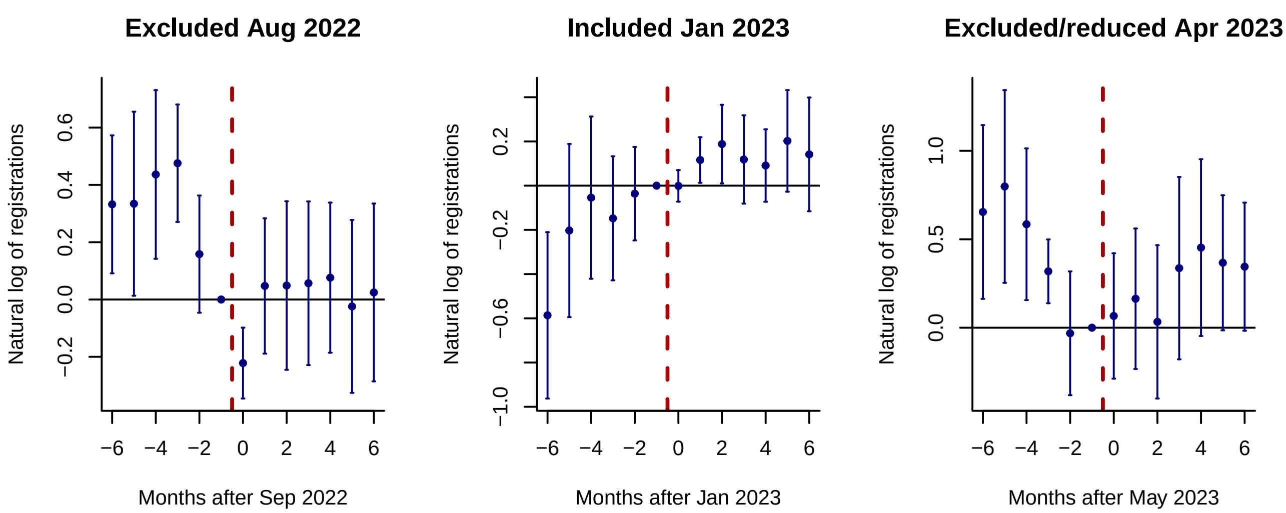
Comparing against the final month before the eligibility change (month -1 on the x-axis), the figures show no statistically detectable evidence of responses to credit eligibility. For the Excluded August 2022 group, the 95 percent confidence intervals rule out registration decreases of more than about 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.

Figure A10: **Registration Trends Associated with Eligibility Changes**

(a) **Trends by Eligibility Group**



(b) **Event Study Estimates**

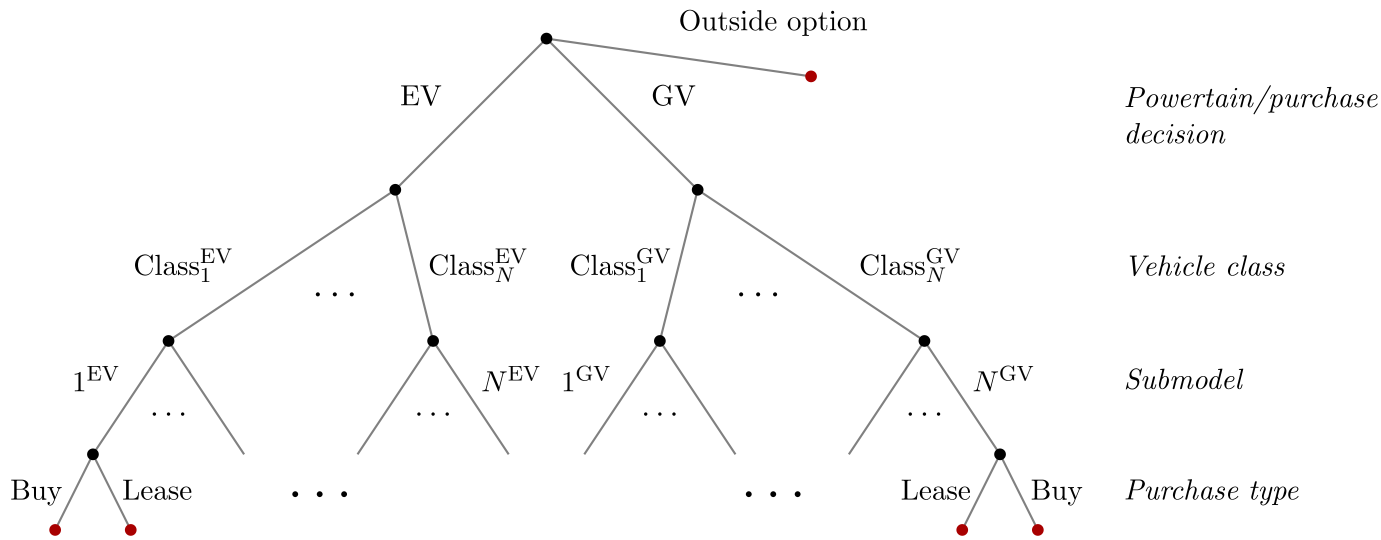


Notes: Panel (a) presents ln(registration) indexes constructed by computing the January 2023 weighted averages for each eligibility group and then recursively adding the sales-weighted average changes for all submodels available in each previous or subsequent month. Panel (b) presents the γ_r^e coefficients and 95 percent confidence intervals from equation (3). Eligibility groups are described in Figure 1. In both panels, we weight submodels by average monthly sales in months when the submodel was available.

D Equilibrium Model

D.1 Quantity Demanded and Consumer Surplus

Figure A11: Nested Logit Structure



There are M consumers in the market indexed by i. Each consumer receives indirect utility from choice j with price p_j and demand subsidy τ_j equal to

$$U_{ij} = \xi_j - \alpha (p_j - \tau_j) + \epsilon_{ij}$$

where ξ_j is a mean consumption utility common to all consumers and ϵ_{ij} is an idiosyncratic preference unique to each consumer distributed standard 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 (5). We normalize the common part of utility of the outside option to zero, so $U_{i0} = \epsilon_{i0}$. To derive the market shares of each product, we first define the following inclusive values, which represent the expected utility of a purchase option within a nest conditional on selecting that nest

$$\begin{aligned}
I_k &= (1-\sigma^k) \ln \sum_{j \in \mathcal{J}_k} \exp\left(\frac{\xi_j - \alpha (p_j - \tau_j)}{1-\sigma^k}\right) \\
I_c &= (1-\sigma^c) \ln \sum_{k \in \mathcal{K}_c} \exp\left(\frac{I_k}{1-\sigma^c}\right) \\
I_g &= (1-\sigma^g) \ln \sum_{c \in \mathcal{C}_g} \exp\left(\frac{I_c}{1-\sigma^g}\right) \\
I &= \ln\left(1 + \exp I_{EV} + \exp I_{GV}\right)
\end{aligned} \tag{15}$$

In the above notation, $\mathcal{J}$ is the set of (1361) options available to purchase or lease; $\mathcal{J}_k$ is the partition of $\mathcal{J}$ corresponding to submodel k in the set of (757) submodels $\mathcal{K}$; $\mathcal{K}_c$ is the partition of $\mathcal{K}$ corresponding to class c in the set of (9) classes $\mathcal{C}$; and $\mathcal{C}_g$ is the partition of $\mathcal{C}$ corresponding to powertrain g in the set of powertrains (i.e., the top-level nesting: GV, EV, or 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, $I_0 = 0$. This is the source of the 1 in the final inclusive value.

Unconditional choice probabilities for j are given by the product of conditional probabilities within a nest and the overall choice probability of powertrain, g:

$$s_j = \underbrace{\frac{\exp\left(\frac{\xi_j - \alpha(p_j - \tau_j)}{1-\sigma^k}\right)}{\exp\left(\frac{I_{k(j)}}{1-\sigma^k}\right)}}_{s_{j|k(j)}} \times \underbrace{\frac{\exp\left(\frac{I_{k(j)}}{1-\sigma^c}\right)}{\exp\left(\frac{I_{c(j)}}{1-\sigma^c}\right)}}_{s_{k(j)|c(j)}} \times \underbrace{\frac{\exp\left(\frac{I_{c(j)}}{1-\sigma^g}\right)}{\exp\left(\frac{I_{g(j)}}{1-\sigma^g}\right)}}_{s_{c(j)|g(j)}} \times \underbrace{\frac{\exp I_{g(j)}}{\exp I}}_{s_{g(j)}} \tag{16}$$

McFadden (1978) provides a full derivation given the CDF of ϵ_{ij}. Total registrations come from multiplying choice probabilities by the number of consumers, $q_j = s_j \times M$. The substitution between any two choices,j and r, given by $\frac{\partial q_j}{\partial p_r}$ in equation (7), can be derived using equations (15) and (16).

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

$$CS = \frac{I}{\alpha} \tag{17}$$

D.2 Estimation

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

$$\xi_j^{(t+1)} \leftarrow \xi_j^{(t)} + \left(1 - \max\left\{\sigma^k, \sigma^c, \sigma^g\right\}\right)\left[\log s_j^{obs} - \log s_j^{(t)}\right] \tag{18}$$

where s_j^{obs} are observed market shares in the data and $s_j^{(n)}$ are implied market shares in the model given current values of $\xi_j^{(n)}$, prices, and the outer loop parameters. In the outer loop, we minimize the sum-squared relative deviation between our four model moments, $m_n(\cdot)$, and our data moments, m_n, $n = 1, ..., 4$

$$\sum_n \left(\frac{m_n(\alpha, \sigma^k, \sigma^c, \sigma^g) - m_n}{m_n}\right)^2 \tag{19}$$

The four moments we match are a market share-weighted model-level own-price demand elasticity, a simulated increase in lease prices for the subset of vehicles excluded from credits in August

2022, the share of EV owners who choose another EV as a second choice if their first choice was unavailable, and 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.

Since our model is at the level of a submodel-by-purchase option, while the moment elasticity is aggregated to the model-level, we simulate the model-level elasticity by raising and lowering prices by 0.5% and taking the average percent change in registrations as the central difference approximation to the elasticity. 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

$$\frac{s_{r\backslash k} - s_r}{s_k} \tag{20}$$

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 $r, k = 1, ..., J$.[28] The share of EV consumers whose second choice is also an EV is then given by

$$D_{EV\to EV} = \frac{\sum_{k\in EV} s_{k\backslash 0}\left(\sum_{r\in EV} s_{r\backslash k,0}\right)}{\sum_{k\in EV} s_{k\backslash 0}} \tag{21}$$

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

$$D_{EV-class\to EV-class} = \frac{\sum_{c\in EV} s_{c\backslash 0}\left(\frac{\sum_{k\in c} s_{k\backslash 0}\left(\sum_{r\in c} s_{r\backslash k,0}\right)}{\sum_{k\in c} s_{k\backslash 0}}\right)}{\sum_{c\in EV} s_{c\backslash 0}} \tag{22}$$

Additional details on the use of second choice shares in estimating substitution patterns can be found in Conlon and Mortimer (2021). Since we have as many moments as parameters to estimate, we match the targeted moments exactly.

Estimation of the supply side consists of inverting the Nash-Bertrand first-order condition in equation (9). In particular, stacking the system of J equations gives the markup equation

$$\boldsymbol{\mu} = -\tilde{\boldsymbol{\Omega}}^{-1}\boldsymbol{q} \tag{23}$$

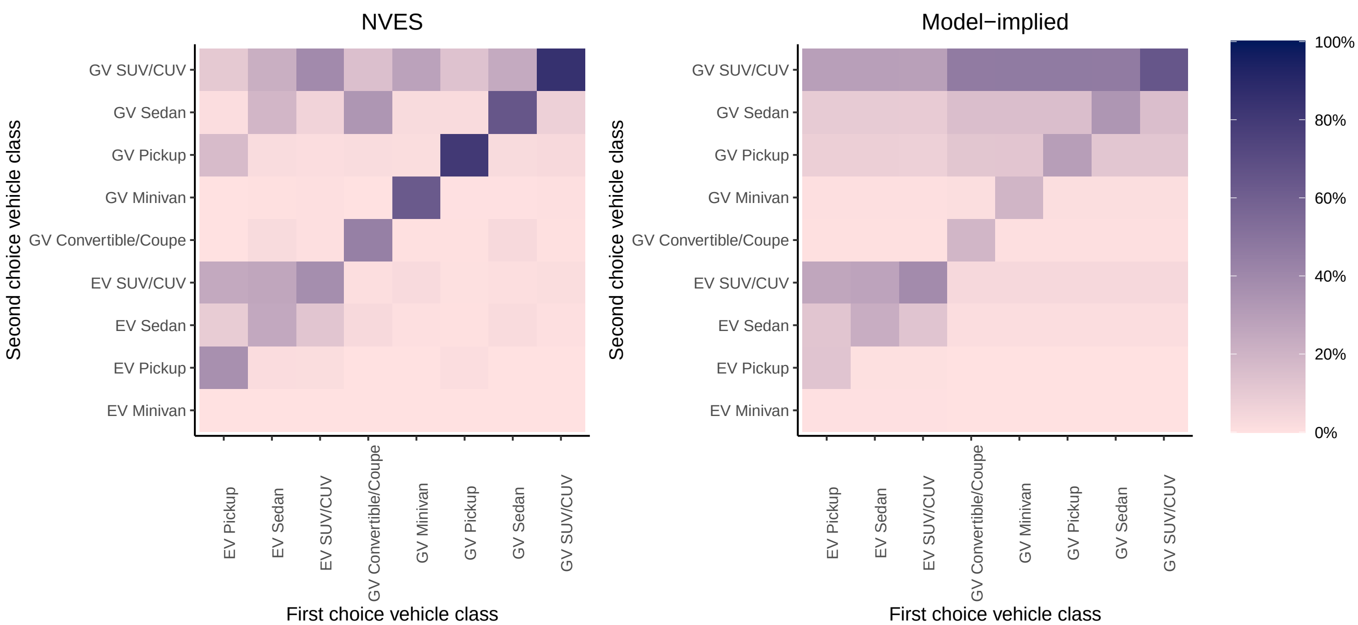
where $\boldsymbol{\mu}$ is a J-vector of markups, $\mu_j = p_j - c_j + \kappa_j$ and $\tilde{\boldsymbol{\Omega}} = \boldsymbol{\Omega} \odot \mathcal{H}$ is the matrix of demand

[28] The proportional substitution in the nested logit to the outside option implies $s_{k\backslash 0} = s_k/(1 - s_0)$.

derivatives multiplied (Hadamard product) by the firm ownership matrix. That is, if $f(j)$ returns the identify of the firm that produces j, then each j, r element is given by $\left[\tilde{\boldsymbol{\Omega}}_{jr}\right] = \frac{\partial q_r}{\partial \tau_j} \times 1_{f(r)=f(j)}$. 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.

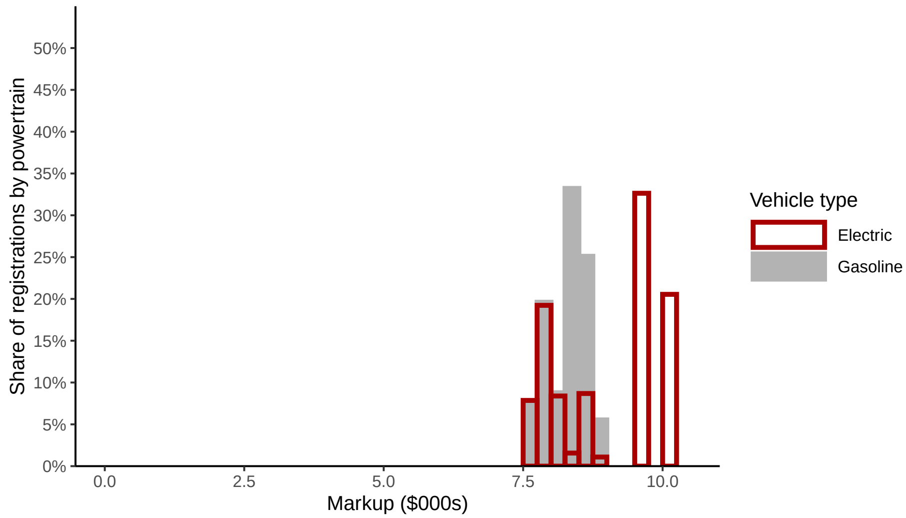
To compute alternative price equilibria in our counterfactuals that change the policy vectors $\boldsymbol{\tau}$ and $\boldsymbol{\kappa}$, we follow the standard approach found in Morrow and Skerlos (2011) and solve a fixed-point problem closely related to equation (23) and which coincides at an equilibrium point.

Figure A12: **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.

Figure A13: **Distribution of Model-Implied Markups for EVs and GVs**



Notes: This figure presents the distribution across submodels of markups implied by firms' first-order condition in equation (9), weighting submodels by registrations in July and August 2023.

D.3 Sensitivity Analysis

The tables below report sensitivity to assumptions on the MCPF, SCC, and demand elasticity.

Table A4: **Counterfactual Simulation Results: Sensitivity Analysis (MCPF and SCC)**

		(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	$1,072	$2,520
2.	ΔGlobal negative externalities	0.52	0.07	-0.29
3.	ΔGlobal surplus	-3.65	-0.13	-0.11
4.	ΔUS total surplus (global SCC)	-2.84	0.04	0.30
5.	Cost per additional EV ($000s/EV)	32.5	24.6	34.9
6.	US MVPF (global SCC)	0.73	1.05	1.14
	Panel (b): Marginal Cost of Public Funds = 1.4, Social Cost of Carbon = $241			
1.	Mean EV subsidy	$7,180	$3,058	$5,449
2.	ΔGlobal negative externalities	-0.87	-0.19	-1.38
3.	ΔGlobal surplus	-2.26	-0.20	0.05
4.	ΔUS total surplus (global SCC)	-1.45	0.30	0.90
5.	Cost per additional EV ($000s/EV)	32.5	26.6	36.1
6.	US MVPF (global SCC)	0.86	1.11	1.17
	Panel (c): Social Cost of Carbon = $100			
1.	Mean EV subsidy	$7,180	$7,450	$10,649
2.	ΔGlobal negative externalities	0.04	0.24	-1.00
3.	ΔGlobal surplus	-0.23	-0.01	0.46
4.	ΔUS total surplus (global SCC)	0.59	1.33	2.36
5.	Cost per additional EV ($000s/EV)	23.2	22.2	27.8
6.	US MVPF (global SCC)	1.08	1.20	1.22
	Panel (d): Social Cost of Carbon = $200			
1.	Mean EV subsidy	$7,180	$9,029	$13,231
2.	ΔGlobal negative externalities	-0.61	-0.42	-2.66
3.	ΔGlobal surplus	0.42	0.30	1.15
4.	ΔUS total surplus (global SCC)	1.24	1.98	3.56
5.	Cost per additional EV ($000s/EV)	23.2	23.3	29.8
6.	US MVPF (global SCC)	1.17	1.22	1.23
	Panel (e): Social Cost of Carbon = $241			
1.	Mean EV subsidy	$7,180	$9,693	$14,331
2.	ΔGlobal negative externalities	-0.87	-0.78	-3.59
3.	ΔGlobal surplus	0.69	0.47	1.52
4.	ΔUS total surplus (global SCC)	1.50	2.29	4.15
5.	Cost per additional EV ($000s/EV)	23.2	23.8	30.7
6.	US MVPF (global SCC)	1.20	1.22	1.24

Notes: This table presents sensitivity analysis for counterfactual simulation results presented in Tables 5 and 6. All results are relative to the scenario with no EV credits, as in Table 6. For each scenario under consideration, we simulate for column 2 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, namely vehicles already eligible under the IRA. "US total surplus" equals "[global] total surplus" minus foreign automakers' producer surplus.

Table A5: **Counterfactual Simulation Results: Sensitivity Analysis (Elasticity and SCC)**

		(1) IRA	(2) US-optimal uniform EV subsidy with 30D restrictions	(3) US-optimal differentiated EV subsidy with 30D restrictions
	Panel (a): Model-Level Elasticity = -4, Social Cost of Carbon = $241			
1.	Mean EV subsidy	$7,180	$12,741	$17,607
2.	ΔGlobal negative externalities	-0.69	-0.91	-3.40
3.	ΔGlobal surplus	0.95	0.70	1.64
4.	ΔUS total surplus (global SCC)	1.80	3.26	5.18
5.	Cost per additional EV ($000s/EV)	29.5	31.6	39.3
6.	US MVPF (global SCC)	1.24	1.22	1.23
	Panel (b): Model-Level Elasticity = -4, Social Cost of Carbon = $28			
1.	Mean EV subsidy	$7,180	$9,285	$12,198
2.	ΔGlobal negative externalities	0.40	0.64	-0.08
3.	ΔGlobal surplus	-0.15	-0.08	0.17
4.	ΔUS total surplus (global SCC)	0.71	1.70	2.60
5.	Cost per additional EV ($000s/EV)	29.5	29.2	34.8
6.	US MVPF (global SCC)	1.10	1.19	1.20

Notes: This table presents sensitivity analysis for counterfactual simulation results presented in Tables 5 and 6. All results are relative to the scenario with no EV credits, as in Table 6. For each scenario under consideration, we simulate for column 2 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, namely vehicles already eligible under the IRA. "US total surplus" equals "[global] total surplus" minus foreign automakers' producer surplus.

Table A6: **Decomposition of Second-Best Uniform Subsidies**

	MCPF = 1.0, SCC = $28	MCPF = 1.4, SCC = $28	MCPF = 1.0, SCC = $241	MCPF = 1.4, SCC = $241
Price distortion	$2,268	$1,431	-$6,562	-$4,884
Indirect substitution	$892	$494	$13,293	$9,051
Subtotal	*$3,160*	*$1,925*	*$6,731*	*$4,167*
Profit shifting	$3,195	$2,572	$2,961	$2,462
Tax distortion	–	-$3,425	–	-$3,570
Uniform subsidy	$6,355	$1,072	$9,693	$3,058

Notes: This table presents the decomposition of second-best 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 2, using equation (38) in the appendix for the more general case of an MCPF greater than one. The combined environmental and markup components sum to the subtotal displayed in row 3. Column 1 corresponds to the uniform subsidy calculated in Table 6. Columns (2), (3), and (4) correspond to uniform subsidies calculated in Table A4 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 9, 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.

E Analytical Model Appendix

Recall CS is consumer surplus, $PS = \sum_j q_j\mu_j$ is firm profits, $G = \eta \sum_j q_j(\tau_j + \kappa_j)$ is government spending under an assumed MCPF, and $E = \sum_j q_j\phi_j$ is negative externalities. As we discuss in the main text, since physical incidence is independent of economic incidence, τ_j and κ_j are perfect substitutes and there are infinite combinations of the two that yield the same welfare. We provide results fixing $\kappa_j = 0$.

E.1 First-Best

To derive the total surplus-maximizing subsidies for the global planner, we take the derivative of W in equation (10) with respect to arbitrary good $j = 1$:

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

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

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

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 takeup of q_1. Doing this for all goods gives a system of equations whose solution is

$$
\eta\tau_j^{FB} = \underbrace{\mu_j}_{\text{markup}} - \underbrace{\phi_j}_{\text{negative externality}} - \underbrace{(\eta - 1)q_j}_{\text{tax distortion}}. \qquad (26)
$$

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, $\eta \times \tau_j^{FB}$, with the total distortion in the economy arising from unpriced externalities and transfers.

E.2 Second Best Differentiated Subsidy

This subsection provides the derivation of Proposition 1, the second best differentiated subsidy for a subset of goods $\mathcal{S}$. We allow the social planner to put no weight on some firms' profits, for example a US planner that prioritizes domestic firms. This nests the global planner solution when all profit changes 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 profits do not contribute to welfare as For:

$$[\tau_1]: \quad \frac{\partial W^{US}}{\partial \tau_1} = \underbrace{q_1 - \sum_j q_j \frac{\partial p_j}{\partial \tau_1}}_{\frac{\partial CS}{\partial \tau_1}} + \underbrace{\sum_j \frac{\partial q_j}{\partial \tau_1}\mu_j + \sum_j q_j \frac{\partial \mu_j}{\partial \tau_1}}_{\frac{\partial PS}{\partial \tau_1}} \tag{27}$$

$$\underbrace{-\eta \sum_{j\in\mathcal{S}} \frac{\partial q_j}{\partial \tau_1}\tau_j - \eta q_1}_{\frac{\partial G}{\partial \tau_1}} \underbrace{- \sum_j \frac{\partial q_j}{\partial \tau_1}\phi_j}_{\frac{\partial E}{\partial \tau_1}} \underbrace{- \sum_{j\in For} \frac{\partial \pi_j}{\partial \tau_1}}_{\frac{\partial PS^{For}}{\partial \tau_1}} = 0$$

Canceling terms as in Section E.1 gives

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

Notice that through the functional form of indirect utility, demand derivatives with respect to subsidies are the negative of derivatives with respect to prices, $\frac{\partial s_j}{\partial \tau_r} = -\frac{\partial s_j}{\partial p_r}$. 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

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

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

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

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 profit impacts on foreign firms corresponding to the final term in equation (29).

Multiplying through by the inverse of $\boldsymbol{\Omega}_S$ gives the optimal second-best differentiated subsidy

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

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

To derive an expression for $\boldsymbol{m}_{For}$, we need to know $\frac{\partial \mu_j}{\partial \tau_r}$, since the change in profits $\frac{\partial \pi_j}{\partial \tau_r} = \frac{\partial q_j}{\partial \tau_r}\mu_j + q_j \frac{\partial \mu_j}{\partial \tau_r}$ 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 profits with respect to subsidies. In Appendix D we show that the solution to the Nash-Bertrand pricing game is determined by the linear system

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

where $\tilde{\boldsymbol{\Omega}}$ is the Jacobian matrix of demand derivatives but modified to contain zeros whenever a firm does not own products j and r. That is, $\tilde{\boldsymbol{\Omega}} = \boldsymbol{\Omega} \odot \mathcal{H}$, 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,

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

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.[29] The challenge is in getting an expression for the term in parenthesis. One can show that the (r, j)-th element of $\boldsymbol{H}_{\tilde{\Omega}}(\boldsymbol{\tau})\boldsymbol{\mu} - \boldsymbol{\Omega}$, 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 $-\tilde{\boldsymbol{\Omega}}^{-1}$, 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 Second Best Uniform Subsidy

This subsection provides the derivation of Proposition 2, the second-best uniform subsidy which imposes the restriction that the subsidy is 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 $\mathcal{S}$:

[29] Starting from equation (7), 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 $s_{r|g(j)} = \frac{s_r}{s_{g(j)}}$, $s_{r|c(j)} = \frac{s_r}{s_{c(j)}}$, and $s_{r|k(j)} = \frac{s_r}{s_{k(j)}}$. 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.

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

Cancelling terms and rearranging gives

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

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

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

Dividing through gives

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

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 (14) when $\eta = 1$, but takes the more general form:

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

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 an MCPF different than one.