Designing Electric Vehicle Subsidies for Equity and Efficiency

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Abstract

Electric vehicle (EV) subsidies have been a central part of global clean energy policy but have raised concerns about regressivity. We evaluate equity-focused EV subsidy designs—buyer income limits, price limits, and *used* EV subsidies—as implemented in many countries, including through the U.S. Inflation Reduction Act (IRA). We show that in a simple theoretical model, resale price changes can make new and used EV subsidies economically equivalent. Using a novel bunching estimator exploiting the IRA used EV tax credit's transaction price limit, we estimate that the credit indeed raised EV resale prices—but only after the credits could be paid immediately at the dealership. Using a detailed structural model of U.S. new and used vehicle markets, we show that new EV subsidies accelerate used EV scrappage instead of only diverting from gasoline vehicles, reducing environmental benefits. Partially for this reason, the modeled marginal value of public funds (MVPF) of the IRA EV tax credits is only 0.95. Income-limited new EV subsidies have relatively high welfare-weighted MVPF.

JEL Codes: H21, H22, H23, H24, L13, L50, L91, Q58.

Keywords: Electric vehicles, Inflation Reduction Act, tax credits, subsidies, economic incidence, tax salience, durable goods, resale markets.

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1 Introduction

A central question faced by policymakers worldwide is how to decarbonize their economies equitably. Many stakeholders advocate for "equitable energy transitions" (e.g., World Economic Forum 2024), and these concerns have shaped parts of the U.S. Inflation Reduction Act (IRA) and other policies worldwide. One key component of global decarbonization policies has been subsidies for clean consumer technologies such as solar panels, batteries, energy efficiency, and electric vehicles (EVs). However, these technologies are often more popular among higher-income consumers, raising concerns that subsidies could be regressive.

Electric vehicle subsidies are perhaps the leading example of this debate. EV subsidies can involve significant government spending: before the IRA's EV tax credits were rescinded in late 2025, they were predicted to cost $70 to $390 billion over ten years (CRFB 2023; Bistline, Mehrotra, and Wolfram 2023). But in the U.S. in 2023, the median new EV buyer's income was twice the national median, meaning that the statutory incidence of new EV tax credits primarily benefits the wealthy. Globally, 52 national or regional governments subsidized new EV purchases in 2024. To address regressivity concerns, most of these policies (including the IRA) included buyer income limits, vehicle price limits, and/or subsidies for buying *used* EVs. Policymakers and analysts have argued that used EV subsidies are more progressive, because lower-income people buy more used cars.[1]

Since vehicle resale prices can adjust in equilibrium, economists might immediately wonder whether the economic incidence of new and used EV subsidies follows their statutory incidence. Perhaps policymakers incorrectly believe a "flypaper theory" of incidence, where subsidy benefits stick where they land.[2] Following Nichols and Zeckhauser (1982), one might also wonder whether "indirect targeting" via subsidizing used goods preferred by lower-income people is more efficient than "direct targeting" via buyer income limits.

This paper provides a comprehensive evaluation of equity-focused EV subsidy designs using a theoretical model, a novel bunching estimator identifying resale price changes, and a detailed structural model of new and used vehicle markets. Our empirical work focuses on the tax credits under the U.S. IRA, but the

[1] In 2021, U.S. Senator Alex Padilla co-sponsored used EV tax credit legislation, which was eventually incorporated into the IRA, on the grounds that the credits would "support our working families by ensuring equitable access" to EVs (Gomez 2021). In introducing the bill, Senator Dianne Feinstein said, "We cannot miss an opportunity to ensure that as we electrify our transportation sector, electric vehicles become an option for all families—not just those who can afford new ones" (Congressional Record 2021). Linn (2021) writes that "expanding [EV] subsidies so they apply to used plug-in vehicles could help make the program more equitable." Rasch (2024), Howard (2025), Lara (2026), and Woodley et al. (2026) similarly describe how used EV tax credits are thought to be valuable for lower-income consumers.

[2] Mankiw's (2021) popular undergraduate textbook says, "Many discussions of tax equity ignore the indirect effects of taxes and are based on what economists mockingly call the *flypaper theory* of tax incidence. According to this theory, the burden of a tax, like a fly on flypaper, sticks wherever it first lands. This assumption, however, is rarely valid."

economic lessons are relevant for governments worldwide. Our analyses are made possible by a unique collection of confidential data, including transaction-level microdata from Cox Automotive covering 32 percent of nationwide dealership sales and large-scale second-choice survey data from the National Vehicle Experience Survey.

In our theoretical model, electric vehicles live for up to two periods ("new" and "used") but may be scrapped after the first. Consumers choose between new EVs, used EVs, and the outside option (gas vehicles, or "GVs"). The resale price and scrap rate are determined in rational expectations equilibrium with new and used EV demand. EV production imposes negative externalities (from CO2 emissions), but EV usage reduces negative externalities relative to GVs. The government can offer new and/or used EV purchase subsidies that are either "universal" (i.e., available to all EV buyers) or limited to buyers with lower incomes.

In equilibrium, resale price changes at least partially offset the differing statutory incidence of new and used EV subsidies: new EV subsidies increase resale supply and thus decrease resale prices (benefiting used EV buyers), while used EV subsidies increase resale demand and thus increase resale prices (benefiting new EV buyers). With fully inelastic scrappage, this offset is exact: universal new and used EV subsidies are *equivalent* in stationary equilibrium. This echoes standard tax equivalence results—intuitively, subsidizing resale market sellers versus buyers has the same economic effect. However, price-responsive scrappage attenuates resale price changes, generating a "flypaper effect" where some economic benefits of new or used EV subsidies do indeed stick with the statutory recipients.

We then derive optimal policies for a government that places weakly higher welfare weights on lower-income consumers. Echoing Diamond (1975) and Allcott, Lockwood, and Taubinsky (2019a), the optimal universal new and used EV subsidies have a Pigouvian corrective motive plus a redistributive motive that depends on demand responses and the covariance between welfare weights and new or used EV demand. Intuitively, because of the flypaper effect where some subsidy benefits stick with recipients, an inequality-averse government optimally increases used relative to new EV subsidies if lower-income people prefer used EVs. The two subsidies also have different corrective effects: new EV subsidies increase used EV scrappage, undoing some environmental benefits, while used EV subsidies keep EVs from being scrapped suboptimally early.

Under additional assumptions, we can theoretically rank policies on the marginal value of public funds (MVPF)—specifically, the welfare-weighted consumer surplus plus externality reduction for a marginal subsidy, per dollar of subsidy spending. Income-limited new EV subsidies have higher welfare-weighted MVPFs than either universal or income-limited used EV subsidies, for two reasons. The first is cost-effectiveness: because fewer lower-income people buy new EVs, new EV subsidies available only to lower-income people have fewer inframarginal consumers for whom the subsidy is just a transfer, with no environmental benefits. The second is distributional: regardless of their statutory targeting, used EV subsidies raise resale prices, which indirectly benefits *all* new EV buyers, who tend to have lower welfare weights. In

this sense, "direct targeting" via income-limited new EV subsidies is preferred over "indirect targeting" via used EV subsidies.

The theory underscores that equilibrium resale market price changes can at least partially undo some policymakers' intuitions about the benefits of used EV subsidies. But to what extent do resale prices *actually* respond to used EV tax credits? To measure this, we exploit another equity-focused component of the IRA's used EV tax credits: they were only available for transactions of $25,000 or less. Using our dealership microdata, we show that this price limit generates slight bunching in the distribution of used EV transaction prices in 2023, and substantial bunching in 2024 and 2025.

Since larger resale market movements should generate more bunching below the $25,000 price limit, we can use the amount of excess mass to identify how much the tax credit increased resale prices. We implement that intuition via a novel bunching estimator that also allows for left digit effects (i.e., expected excess mass below round numbers). Counter to the theory but consistent with the descriptive bunching evidence, we estimate that the tax credit had very limited effect on resale prices in 2023. However, the resale price shift increased sharply at the beginning of 2024, when the tax credit could be paid out immediately at the dealership instead of claimed on next year's taxes. One potential explanation for these results is that consumers pay more attention to money paid now instead of later. This underscores the importance of tax credit *delivery*, not just the *amount*.

To quantitatively evaluate counterfactual policies, we generalize the theory into a detailed structural model. The choice set includes all light-duty EVs and GVs aggregated by brand, body style, powertrain, and age (from new to age 19). We estimate a logit demand system with income heterogeneity and random coefficients on key characteristics (including EVs versus GVs and new versus used vehicles) identified from our second-choice survey data. We incorporate the empirical distribution of how long consumers hold vehicles before reselling; this allows us to realistically model the IRA used EV tax credits, which were only available for EVs being resold for the first time. We import a scrap elasticity of -0.7 from Jacobsen and van Benthem (2015). We estimate each vehicle's pollution, accident, and energy pricing externalities following Allcott et al. (2024), assuming a $241 social cost of carbon. We simulate EV subsidies in both a stationary equilibrium (with choice sets and prices constant over time) and a non-stationary equilibrium that captures EV market growth and time-limited subsidies.

There are four key results. First, in stationary equilibrium, universal (i.e., not income-limited) used EV subsidies that are available on the vehicle's first resale are similar to new EV subsidies. This is because about 78 percent of new vehicles are first resold in under 10 years, but such young vehicles are not at much risk of scrappage. Thus, the inelastic scrappage assumption required for theoretical equivalence is approximately correct. In non-stationary equilibrium, however, a used EV subsidy that is available on the vehicle's first resale *after policy implementation* (as under the IRA) can reduce scrappage of used EVs that were already older when the policy was implemented.

Second, additional new EVs generate environmental benefits only to the extent that they reduce gasoline vehicle use instead of accelerating scrappage of used EVs. In stationary equilibrium, new EV subsidies increase new EV sales by 59 percent more than they increase total (new and used) EV ownership. Put differently, for every vehicle-year that new EV subsidies reduce GV use, they also reduce EV use by 0.59 vehicle-years through accelerated scrappage. This accelerated scrappage effect substantially reduces optimal EV subsidy levels. In alternative simulations that (counterfactually) assume fully inelastic scrappage, the welfare gains from new EV subsidies are 134 percent larger. Much of the existing research evaluating EV tax credits models only new vehicle markets (e.g., Xing, Leard, and Li 2021; Allcott et al. 2024; Barwick, Kwon, and Li 2024; Hahn et al. 2026; Kwon 2023), making implicit assumptions analogous to fully inelastic EV scrappage. This result parallels arguments by Gruenspecht (1982), Jacobsen (2013), and Jacobsen and van Benthem (2015) showing that resale market feedbacks are important for evaluating other environmental regulations in auto markets.

Third, partially because of this accelerated scrappage, new and used EV subsidies both have relatively low modeled MVPFs of 1.04 in stationary equilibrium. Alternative subsidy designs that more closely approximate first-best externality taxes could deliver slightly higher MVPFs. An optimal one-time EV production tax paired with an annual EV registration subsidy, which better matches the timing of EVs' negative production externalities versus usage externality reductions, has an MVPF of 1.05. Letting that policy be differentiated for cars versus trucks, which better matches the larger externalities from larger vehicles, further increases the MVPF to 1.07. Since EVs are only a small part of the overall auto market, EV subsidies generate only a fraction of the total surplus gains in the model's social optimum.

Fourth, without income or price limits, both new and used EV subsidies are regressive. In stationary equilibrium, universal new and used EV subsidies both generate more than five times more per-capita surplus gains for consumers with incomes above $150,000 than for consumers with lower incomes. As a result, assuming welfare weights inversely proportional to income, the welfare-weighted MVPF of new EV subsidies is substantially below the unweighted MVPF: 0.69 versus 1.04, respectively. However, as predicted by the theory, income-limited new EV subsidies have a considerably higher welfare-weighted MVPF of 1.14. In a final simulation that most closely matches the original IRA legislation (both new and used subsidies with income and price limits in non-stationary equilibrium), the IRA subsidies have unweighted and welfare-weighted MVPFs of 0.95 and 0.79, respectively. Thus, in our model, the IRA EV subsidy design is both economically inefficient and regressive.

A key caveat is that our analyses assume that the government cannot fully address distributional concerns through more progressive income taxation. Put differently, we apply the theoretical lens of Diamond (1975), not Atkinson and Stiglitz (1976). In addition to addressing the actual policy debate about regressive EV subsidies, our analyses are formally justified if any of the following is true: (i) people don't think about EV subsidies when they choose education or labor supply (Allcott, Lockwood, and Taubinsky 2018); (ii) at least

some of the correlation between income and EV demand is driven by preference heterogeneity (e.g., cultural or environmentalist preferences), not causal income effects (Allcott, Lockwood, and Taubinsky 2019a); or (iii) the government cannot frictionlessly adjust the income tax schedule when it sets EV subsidies.

Our work builds on several literatures. First and most directly, we extend the literature on EV subsidies and the incidence of clean vehicle tax credits.[3] Important papers by Nehiba and Tyndall (2024) and Berman, Hickok, and Nguyen (2025) study other facets of the used EV tax credits.[4] Second, we extend the broader literature on environmental policy in auto markets.[5] Third, we extend the literature on Inflation Reduction Act evaluations.[6] Fourth, we connect to the literature on distributional effects of energy policy and other corrective taxes.[7] Fifth, our finding of increased effects of tax credits after dealership transfer in 2024 may relate to the literature on tax salience.[8] Finally, our structural model builds on other structural models of resale markets for autos and other goods.[9]

Sections 2–8, respectively, present the policy background, theoretical model, data, bunching estimates of short-run price effects, structural model setup and estimation, counterfactual simulations, and conclusion.

[3]Research on EV subsidies includes Gallagher and Muehlegger (2011), Jenn, Azevedo, and Ferreira (2013), Holland et al. (2016), DeShazo, Sheldon, and Carson (2017), Jenn, Springel, and Gopal (2018), Clinton and Steinberg (2019), Springel (2021), Muehlegger and Rapson (2022), Cole et al. (2023), Li (2023), Kwon (2023), Slowik et al. (2023), Allcott et al. (2024), Head et al. (2026), Barwick et al. (2025), and Barwick, Kwon, and Li (2024). Research on the incidence of clean vehicle tax credits includes Sallee (2011), Gulati, McAusland, and Sallee (2017), and Barwick et al. (2023).

[4]Nehiba and Tyndall (2024) present difference-in-differences estimates of the pass-through of the IRA used EV tax credits to the offer price of used EVs in an online marketplace. In contrast, we study actual transaction prices using a bunching estimator. Berman, Hickok, and Nguyen (2025) present theoretical and structural analyses of used EV tax credits, including propositions analogous to Proposition 1 of this paper and Corollary 1 of our 2024 working paper (Allcott, Kwon, and Snyder 2024). Their models focus on endogenizing vehicle owners' choice of when to resell their vehicles, while we assume that holding times are exogenous.

[5]This includes Goldberg (1998), Bento et al. (2009), Jacobsen (2013), Jacobsen and van Benthem (2015), Ito and Sallee (2018), Linn (2022), Lin and Linn (2023), Jacobsen et al. (2023), Armitage and Pinter (2026), and Ito et al. (2026).

[6]This includes Jenkins et al. (2022), Bistline, Mehrotra, and Wolfram (2023), and Bistline et al. (2023).

[7]Research on the distributional effects of energy policies includes Poterba (1991), Borenstein (2012), Borenstein and Davis (2012, 2016, 2025), Davis and Knittel (2019), Goulder et al. (2019), and Borenstein, Fowlie, and Sallee (2022). Research on the distributional effects of other corrective taxes includes Gruber and Kőszegi (2004) and Goldin and Homonoff (2013) on cigarette taxes and Allcott, Lockwood, and Taubinsky (2019a) on soda taxes.

[8]This includes Chetty, Looney, and Kroft (2009), Finkelstein (2009), Goldin and Homonoff (2013), Taubinsky and Rees-Jones (2018), Homonoff (2018), and Kroft et al. (2024).

[9]This includes Hendel and Lizzeri (1999), Stolyarov (2002), Esteban and Shum (2007), Schiraldi (2011), Chen, Esteban, and Shum (2013), Gavazza, Lizzeri, and Roketskiy (2014), and Gillingham et al. (2023) on auto resale markets, and Hendel and Nevo (2006), Gavazza (2011), and Gowrisankaran and Rysman (2012) on other markets.

2 Policy Background

Governments worldwide have devoted significant spending to electric vehicle purchase subsidies, including rebates, tax credits, and waived taxes. Central governments worldwide spent $186 billion on EV subsidies from 2017 to 2024 (IEA 2025). China alone spent $183 billion on EV subsidies from 2009 to 2023 (CSIS 2024). As described above, before the IRA's EV tax credits were rescinded in late 2025, they were forecasted to cost $70 billion to $390 billion over 10 years (CRFB 2023; Bistline, Mehrotra, and Wolfram 2023).

As detailed in Appendix A, new EV buyers are relatively wealthy: in the U.S. in 2023, the median new EV buyer had household income of $152,000, about 2.5 times the median U.S. household income of $76,000. However, used car buyers were less wealthy: median household incomes for new and used car buyers were $116,000 and $71,000, respectively.

Policymakers have long been concerned about the equity and salience of energy tax credits. Indeed, the U.S. Congress debated these issues in 1977 when evaluating energy tax credits implemented in response to the 1970s energy crises. As quoted in McIntyre (1981), Representative Barber Conable worried about equity, saying that solar space heating tax credits are "a kind of rich man's plaything." Representative Bill Frenzel worried about salience, saying that "The tax credit does not motivate, but rather simply occurs at the end of the year when the fellow finds there was a tax credit available."

Given these issues, while many governments around the world subsidize EV purchases, many also have added equity-focused components to their policies. Table 1 presents the list of EV subsidies (specifically, purchase rebates or tax credits) available worldwide at any point in 2024. By our count, 52 governments offered subsidies for new EVs in 2024: 25 national governments including the U.S., 16 U.S. states, and 11 regional governments in other countries. Of those 52 policies, 26 also included used EV subsidies, 17 had income limits, and 41 had price limits.

U.S. Inflation Reduction Act EV tax credits. While equity-focused EV subsidy designs are common worldwide, our empirical analyses focus on the U.S. The U.S. federal government offered tax credits of up to $7,500 for buying new EVs starting in 2008. The 2022 Inflation Reduction Act kept the $7,500 amount but modified these new EV tax credits in various ways, including adding two equity-focused components beginning January 1, 2023. First, the IRA added buyer income limits: to qualify, new EV buyers needed to have modified Adjusted Gross Income (AGI) below $300,000 for married couples filing jointly, $225,000 for household heads, and $150,000 for all other taxpayers. Second, the IRA added vehicle price limits: to qualify, new EVs had to have Manufacturer's Suggested Retail Prices (MSRP) below $55,000 (for cars) and $80,000 (for SUVs and trucks).

The IRA also added parallel tax credits for buying used EVs, beginning January 1, 2023. The tax credit amount was $4,000 or 30 percent of price, whichever was less. To be eligible, the vehicle had to be at least

Table 1: **New and Used Electric Vehicle Subsidies Worldwide in 2024**

Location	(1) New subsidy	(2) Used subsidy	(3) Income limit	(4) Price limit	Location	(5) New subsidy	(6) Used subsidy	(7) Income limit	(8) Price limit
Europe					New Brunswick	$3,657	$1,828		✓
Austria	$5,368			✓	Newfoundland & Lab.	$1,828	$1,828		
Croatia	$9,662			✓	Nova Scotia	$2,194	$1,463		✓
Cyprus	$9,662	$9,662		✓	Northwest Terr.	$3,657			✓
France	$4,294		✓	✓	Prince Edward Isl.	$3,657	$3,657		✓
Flanders, Belgium	$4,294	$3,220		✓	Quebec	$2,926	$1,463		✓
Greece	$8,588				Yukon	$3,657			
Iceland	$6,480	$5,040		✓					
Ireland	$3,757			✓	**Australia**				
Italy	$4,831		✓		Queensland	$4,004		✓	✓
Lithuania	$5,368	$2,684		✓	Western Australia	$2,336			✓
Luxembourg	$8,588								
Malta	$11,808				**United States**				
Netherlands	$3,167	$2,147		✓	US (federal)	$7,500	$4,000	✓	✓
Poland	$9,960		✓	✓	California	$7,500	$7,500	✓	✓
Portugal	$4,294			✓	Colorado	$6,000			✓
Romania	$6,709				Connecticut	$4,500	$5,000	✓	✓
Slovenia	$7,729	$3,220		✓	Delaware	$2,500	$2,500		✓
Spain	$9,662			✓	Illinois	$4,000	$4,000		
					Maine	$7,500	$2,500	✓	✓
Asia					Maryland	$3,000			✓
Singapore	$18,455	$18,455			Massachusetts	$5,000	$5,000	✓	✓
Japan	$5,270			✓	Minnesota	$2,500	$600		✓
Thailand	$2,900			✓	New Jersey	$4,000		✓	✓
China	$2,752				New York	$2,000			✓
South Korea	$4,709		✓	✓	Oregon	$7,500	$5,000	✓	
					Pennsylvania	$4,000	$4,000	✓	✓
Canada					Rhode Island	$3,000	$2,500	✓	✓
Canada (federal)	$3,657			✓	Vermont	$5,000	$5,000	✓	✓
British Columbia	$2,926		✓	✓	Washington	$5,000	$2,500	✓	✓
Manitoba	$2,926	$1,828		✓	Electric utilities	various	various	✓	✓

Notes: This table presents the list of EV subsidies available worldwide at any point in 2024. We only include regions that offered purchase subsidies through direct rebates or tax credits; we exclude other incentives such as VAT waivers, import tax waivers, or income tax deductions. Reported subsidy amounts are the maximum offered. To construct this list, we began with existing lists such as Threewitt and Vincent (2024) for the U.S. and European Commission (2024) for Europe, augmented via Google searches for "EV tax credits in X" for every province in Canada, state in Australia, and all other continents, and then confirmed details from official government websites.

two years old—that is, having a model year at least two years before the transaction date. The purchase had to be from a licensed dealership, not from a private party seller. The purchase had to be made for the purpose of using the vehicle in the U.S., rather than reselling, scrapping, or exporting it. The transaction had to be the vehicle's first resale since the IRA passed on August 16, 2022, as documented on a vehicle history report. This prevented people from gaming the credit by repeatedly trading the same vehicle.

The used EV tax credit also had buyer income and vehicle price limits. The buyer income limits were halved relative to the new EV credits: to qualify, used EV buyers needed to have AGI below $150,000 for married couples filing jointly, $112,500 for household heads, and $75,000 for all other taxpayers. The used EV transaction price had to be $25,000 or less.

In 2023, the only way for buyers to receive the new or used EV tax credits was to claim them on personal income taxes the next year. The tax credits were non-refundable, meaning that people must have sufficient personal income tax liability to claim the credit. Starting January 1, 2024, buyers could transfer the EV tax credits to the dealership, in exchange for a lower price or cash rebate. This "dealership transfer" option delivered the financial benefit sooner (immediately upon purchase instead of on the next year's income taxes) and possibly more salient. Moreover, while the buyer income limits and all other eligibility requirements remained, buyers could transfer the tax credits to the dealership even if they did not have personal income tax liability.

Under the Trump Administration's One Big Beautiful Bill Act, both the new and used EV tax credits ended on September 30, 2025.

3 Theoretical Model

3.1 Setup

This section presents a simple theoretical model of subsidies for new versus used electric vehicles. We use the model to build intuition for incidence, optimal policy, and welfare.

Vehicles, externalities, and subsidies. We let t index periods. Throughout the paper, we assume no time discounting. In this section, EVs are undifferentiated products that can be used for up to two periods. We index these new and used ages by $a \in \{n, u\}$. Consumers choose between new EVs, used EVs, and the outside option (a gas vehicle).

EVs impose a one-time negative production externality ϕ_n. For each period of use, EVs reduce negative externalities by ϕ relative to the GV.[10] The government offers new and used EV purchase subsidies $\{\tau_n, \tau_u\}$,

[10]This setup abstracts away from the distinction between new and used GVs. In the simulations in Section 7, EV subsidies have very limited effects on GV scrap rates. Thus, to interpret the theoretical results below, one could think of ϕ as the difference between the EV per-period usage externality and the GV annualized total (production + usage) externality.

which are paid to buyers and financed through lump-sum taxes.

New vehicle supply. In the body of the paper, we assume that new EVs are supplied in perfect competition, with constant price p_{nt} equal to marginal cost. In the appendix, the proofs of all propositions generalize this by assuming that new EVs are produced in symmetric imperfect competition (Genesove and Mullin 1998; Weyl and Fabinger 2013).

Resale and scrappage. At the end of its first period, each vehicle receives a wear-and-tear draw $\zeta \sim G$. The owner then chooses between reselling or scrapping it. Reselling earns the used market price p_{ut}, but the vehicle must first be reconditioned to sellable quality at cost $\zeta\psi$. Scrapping earns scrap value v^s. Scrapped vehicles generate no negative externality reduction and receive no used EV subsidy.

A vehicle will be resold if $p_{ut} - \zeta\psi \geq v^s$, and scrapped otherwise. Thus, the scrap rate is $g(p_{ut}) = 1 - G(\frac{p_{ut}-v^s}{\psi})$. Higher used vehicle prices weakly reduce scrappage: $g' \leq 0$. We let tildes indicate consumers' expectations of future prices; for example, the expected used vehicle market price in period $t+1$ is $\tilde{p}_{u,t+1}$. In period t, a new vehicle's expected value in period $t+1$ is

$$\tilde{v}_{t+1}(\tilde{p}_{u,t+1}) = \underbrace{g(\tilde{p}_{u,t+1})}_{\text{scrap prob}} \cdot \underbrace{v^s}_{\text{scrap value}} + \underbrace{\Big(1 - g(\tilde{p}_{u,t+1})\Big)}_{\text{resale prob}} \cdot \Big(\underbrace{\tilde{p}_{u,t+1}}_{\text{resale value}} - \underbrace{\psi \mathbb{E}[\zeta | \tilde{p}_{u,t+1} - \zeta\psi \geq v^s]}_{\text{reconditioning cost}} \Big). \quad (1)$$

After their second period, all remaining vehicles are scrapped, with the owner receiving v^s.

Demand. There is a unit mass of consumers with income types indexed by i. To simplify aggregation, we assume quasilinear utility and that all consumer types purchase at least some of both vehicle ages and have linear demands with the same own and cross-price slopes. We assume that new and used subsidies have the same eligibility conditions. Define $e_i \in \{1, 0\}$ as an indicator for whether type i is eligible for the subsidies, and define $\mu > 0$ as the share of consumers that are eligible. Type i's expected new and used vehicle rental prices are $\tilde{r}_{int} = p_{nt} - e_i\tau_{nt} - \tilde{v}_{t+1}$ and $r_{iut} = p_{ut} - e_i\tau_{ut} - v^s$, respectively, giving demand functions $D_{ia}(\tilde{r}_{int}, r_{iut})$ for each age. The average new and used rental prices are $\tilde{r}_{nt} = p_{nt} - \mu\tau_{nt} - \tilde{v}_{t+1}$ and $r_{ut} = p_{ut} - \mu\tau_{ut} - v^s$, giving aggregate demand functions $D_a(\tilde{r}_{nt}, r_{ut})$.

Define $D'_a < 0$ as the own-price response: the derivative of D_a with respect to age a average rental price r_a. Define $D'_c > 0$ as the cross-price response: the derivative of D_a with respect to the other age's average rental price. Under quasilinear utility, Slutsky symmetry implies that the two cross-price responses are equal. Our propositions assume $(1-g) \cdot |D'_a| > D'_c$, which requires that there be sufficient substitution between EVs and GVs.

Equilibrium. An equilibrium is a set of prices $\{p_{nt}, p_{ut}\}$ such that (i) new vehicle buyers correctly forecast the resale price, i.e. $\tilde{p}_{u,t+1} = p_{u,t+1}$, and (ii) the used vehicle market clears, i.e. $D_{ut} = (1-g)D_{n,t-1}$. All propositions in this section focus on the stationary equilibrium, defined as $p_{at} = p_a, \forall\{a, t\}$.

3.2 Incidence

Appendix B.1 presents initial comparative statics that drive our results: new EV subsidies weakly decrease EV resale prices p_u (both by shifting demand away from used EVs and by increasing their supply), while used EV subsidies weakly increase p_u (by increasing demand for used EVs). Thus, new EV subsidies weakly increase scrap rates, while used EV subsidies weakly decrease them.

The economic incidence of EV subsidies is determined by how they affect rental prices—the net costs of owning EVs. Proposition 1 characterizes these effects.

Proposition 1. *The stationary equilibrium rental price effects are*

$$(1-g)\frac{dr_n}{d\tau_n} \leq \frac{dr_n}{d\tau_u} < 0,$$
$$\frac{dr_u}{d\tau_u} \leq (1-g)\frac{dr_u}{d\tau_n} < 0.$$

If scrappage is fully inelastic ($g' = 0$), the survival-adjusted rental price effects are equal:

$$(1-g)\frac{dr_n}{d\tau_n} = \frac{dr_n}{d\tau_u},$$
$$\frac{dr_u}{d\tau_u} = (1-g)\frac{dr_u}{d\tau_n}.$$

Proof: see Appendix B.2.

The expressions in Proposition 1 deflate the new EV subsidy effects by the vehicle survival probability $(1-g)$ because only $(1-g)$ as many buyers receive used subsidies as receive new subsidies.

Proposition 1 has three implications. First, both new and used EV subsidies reduce the average rental prices for both ages. New EV subsidies directly reduce new EV rents but also indirectly reduce used EV rents by decreasing used EV prices. Used EV subsidies directly reduce used EV rents but also indirectly reduce new EV rents by increasing used EV prices. Thus, the subsidies directly benefit statutory recipients and also indirectly benefit all buyers of the other age.

Second, if scrappage is fully inelastic ($g' = 0$), then new and used subsidies have equivalent survival-adjusted rental price effects. This is a corollary of standard tax equivalence results: the economic incidence of EV subsidies is independent of whether the statutory incidence is on used EV buyers or sellers.[11] By extension, with $g' = 0$ any linear combination of subsidies with the same value of $\tau_n + (1-g)\tau_u$ has the same rental price effect.

[11] If all consumers are eligible ($\mu = 1$), then $(1-g)d\tau_n$ and $d\tau_u$ result in the same allocations. If some consumers are ineligible ($\mu < 1$), then the rental price effects are equivalent but the allocations differ across consumers. A subsidy with partial eligibility harms ineligible buyers of the same age vehicle, because the gross-of-subsidy rental price increases.

Third, if scrappage is not fully inelastic ($g' < 0$), the survival-adjusted rental price decreases are larger for subsidies to the corresponding age than subsidies to the other age. For intuition, consider the extreme case where scrappage is infinitely elastic, so the used vehicle price p_u is fixed. In that case, a universal τ_n decreases r_n one-for-one and leaves r_u unaffected, while a universal τ_u symmetrically decreases r_u one-for-one and leaves r_n unaffected. Thus, elastic scrappage generates a kind of "flypaper effect," where the economic benefits stick with the statutory recipients.

3.3 Welfare and Optimal Policy

We now consider welfare and optimal policy. The social planner applies welfare weights w_i to type i's consumer surplus, with average $\bar{w} = 1$. Higher-income types receive weakly lower weight. Welfare W equals welfare-weighted consumer surplus plus negative externality reductions, net of government spending.

3.3.1 Optimal Subsidies with Full Eligibility

Proposition 2 presents optimal subsidy levels when all consumer types are eligible.

Proposition 2. *If scrappage is not fully inelastic ($g' < 0$), the welfare-maximizing universal subsidies in stationary equilibrium satisfy*

$$\tau_n^* = \overbrace{\phi - \phi_n}^{\textit{corrective motive}} + \overbrace{\frac{\textit{Cov}(w_i, D_{in}) - \textit{Cov}(w_i, D_{iu}) \cdot D_c'/D_u'}{-D_n' + D_c'^2/D_u'}}^{\textit{redistributive motive}},$$

$$\tau_u^* = \phi + \frac{\textit{Cov}(w_i, D_{iu}) - \textit{Cov}(w_i, D_{in}) \cdot D_c'/D_n'}{-D_u' + D_c'^2/D_n'}.$$

If scrappage is fully inelastic ($g' = 0$), any pair $\{\tilde{\tau}_n, \tilde{\tau}_u\}$ satisfying $\tilde{\tau}_n + (1-g)\tilde{\tau}_u = \tau_n^* + (1-g)\tau_u^*$ maximizes welfare.

Proof: see Appendix B.3.

Echoing Allcott, Lockwood, and Taubinsky (2019a), Proposition 2 shows that there are two reasons to subsidize EVs: the corrective and redistributive motives. To isolate the corrective motive, consider the case where all consumers have the same welfare weight, so $\text{Cov}(w_i, D_{ia}) = 0$. This delivers the standard Pigouvian result that optimal corrective subsidies exactly internalize externalities.

The $\tau_u^* = \phi$ result in Proposition 2 demonstrates the efficiency rationale for used EV subsidies. Driving used EVs reduces negative externalities relative to the outside option, so unless scrappage is perfectly inelastic ($g' = 0$), used EVs will be scrapped suboptimally early without a subsidy to keep them on the road. Indeed, Section 6.4 reports that the EV manufacturing externality is several times larger than the EV-GV

yearly externality difference, so $\phi - \phi_n < 0$ and it would be optimal to *tax* new EVs while subsidizing used EVs.

Now add the redistributive motive. For intuition, first consider the special case where $D_c' = 0$, meaning that new and used EVs are unrelated goods. In that case, the redistributive motive terms for the new and used subsidies are $\frac{Cov(w_i, D_{in})}{-D_n'}$ and $\frac{Cov(w_i, D_{iu})}{-D_u'}$, respectively, and we have an analogue to the Diamond (1975) "many-person Ramsey tax rule."[12] The numerator of those terms is $\text{Cov}(w_i, D_{ia})$: if consumers with high welfare weights (i.e., low incomes) have higher demand, then the optimal subsidy is more positive. The denominator is the demand response D_a'; if demand is more responsive, then using the subsidy to redistribute generates more deadweight loss, and the optimal deviation from the corrective level is thus smaller.

In the more general case with $D_c' > 0$, the numerator of the redistributive motive for τ_n^* also accounts for how that subsidy affects used EV rents, interacted with the welfare weights on used EV buyers. The denominator also accounts for the efficiency consequences of changes in used EV demand. The adjustments for τ_u are symmetric.

Appendix B.3 shows that the redistributive motive term is more negative for τ_n^* than for τ_u^* if higher-income people more strongly prefer new EVs, after rescaling by the market demand slopes. For intuition, notice that because high-income consumers buy more new EVs, an inequality-averse planner places lower value on reducing r_n than on reducing r_u. Through the flypaper effect described above, τ_n reduces r_n more, while τ_u reduces r_u more. This provides a qualified theoretical rationale for some policymakers' interest in subsidizing used EVs for distributional reasons.

The final part of Proposition 2 states that if scrappage is perfectly inelastic, the equivalence result from Proposition 1 implies that any appropriate linear combination of subsidies can maximize welfare. For example, one optimal corrective policy would be $\tau_u = 0$ and τ_n set to the expected lifetime externality reduction: $\tau_n = (2 - g)\phi - \phi_n$.

3.3.2 Second-Best Optimal New EV Subsidies

In Proposition 2, the government can subsidize both EV ages and achieve the social optimum. In reality, EVs live for more than two periods, and the IRA's new and used EV transaction subsidies do not optimally correct prices at all ages. This issue plays an important role in the simulations in Section 7. To provide intuition for the effects of an inability to subsidize EVs at all ages, Proposition 3 derives the optimal corrective τ_n^* while restricting $\tau_u = 0$.

Proposition 3. *If $\tau_u = 0$ and all consumers have equal welfare weights w_i, the welfare-maximizing univer-*

[12] See Appendix B.4 for details on this analogy.

sal τ_n in stationary equilibrium satisfies

$$\tau_n^{**} = \overbrace{\Big(\underbrace{2-g}_{\substack{\text{expected life} \\ \text{of new EV}}} - \underbrace{\frac{D_n \cdot dg/d\tau_n}{dD_n/d\tau_n}}_{\substack{\text{used EV years lost from} \\ \text{accelerated scrappage}}} \Big)}^{\substack{\text{GV-EV usage substitution} \\ \text{from marginal new EV sale}}} \phi - \phi_n.$$

Proof: see Appendix B.5.

Proposition 3 states the intuitive result that the optimal corrective subsidy τ_n^{**} equals the externality reduction from the marginal new EV sale, which is the usage externality reduction relative to GVs (the first term) minus the manufacturing externality ϕ_n. The term inside parentheses is the substitution of vehicle usage-years from GVs to EVs from the marginal new EV sale. This is the expected life of that new EV minus the used EV years lost from accelerated scrappage. Thus, τ_n^{**} depends on the share of marginal new EV sales that are diverted from GVs versus used EVs. On one extreme where scrappage is fully inelastic ($dg/d\tau_n = 0$), diversion is entirely from GVs, and τ_n^{**} is the GV-EV lifetime externality difference $(2-g)\phi - \phi_n$. However, on the other extreme where diversion is entirely from used EVs, there is no reduction in usage externalities from GVs, and it is optimal to *tax* new EVs by the production externality ϕ_n.

3.3.3 Welfare Effects of Income Limits

Appendix B.6 presents optimal subsidies when the government can set different subsidies for each income type. This delivers a result where the redistributive motive term is more positive for subsidies for lower-income people, echoing Ferey, Lockwood, and Taubinsky (2024). One basic implication is that a government that can freely vary subsidies by income would not optimally choose a uniform subsidy with an income limit, as observed under the Inflation Reduction Act and in many other countries shown in Table 1. Instead, the theoretical optimum involves subsidies that decrease smoothly with income and may be positive or negative depending on the strength of the corrective and redistributive motives. One natural reason for the observed subsidy structure is a need for simplicity.

Given the observed structure, a key question is whether income limits are desirable, and whether equity goals are best achieved directly (through income limits) or indirectly (through subsidizing used EVs). Proposition 4 speaks to this by comparing the welfare-weighted MVPF (specifically, welfare-weighted consumer surplus plus negative externality reductions per dollar of subsidy spending) from marginal new versus used EV subsidies with and without income limits. Define M_a^F as the welfare-weighted MVPF for a marginal subsidy with full eligibility for age a EVs, and define M_a^L as the welfare-weighted MVPF for a marginal income-limited subsidy for age a EVs, both evaluated at $\tau_n = \tau_u = 0$.

Proposition 4. *Under the conditions specified in Appendix B.7, including* $(2-g)\phi-\phi_n > 0$ *and sufficiently inelastic scrappage,*

$$M_n^L > \begin{cases} M_n^F \\ M_u^F \\ M_u^L. \end{cases}$$

Proof: see Appendix B.7.

The proposition states that of these four policies, income-limited new EV subsidies have the most positive effect on social welfare per dollar of government spending. The proposition holds for two reasons. The first is cost-effectiveness: income-limited new EV subsidies sell more new EVs (and thus reduce externalities more) per dollar of government spending, because lower-income consumers are less likely to buy new EVs at baseline, and thus a smaller share of subsidy spending goes to inframarginal consumers whose purchases are unaffected. The second is distributional, driven by the indirect rent benefits shown in Proposition 1 (both subsidies lower rents for all buyers of the *other* age): τ_n indirectly benefits all used EV buyers (who have lower average income and thus higher welfare weight w), while τ_u indirectly benefits all new EV buyers (who have higher average income and lower w).

Put differently, even an income-limited used EV subsidy does not actually limit the benefits only to lower-income people, because the benefits leak to higher-income new EV buyers through equilibrium resale price adjustments. Within these four policy options, the only way to avoid benefiting higher-income new EV buyers is to have an income-limited new EV subsidy.

3.4 Comments

Two types of inattention could affect this section's predictions. First, if consumers are inattentive to a subsidy, uncertain about eligibility, or discount it because it's received in the future, this would mute all price and quantity effects and provide a windfall to subsidy recipients. We return to this possibility in Section 5 when discussing the large effects of dealership transfer on EV resale prices in 2024. Second, if new EV buyers are inattentive to the equilibrium effects of EV subsidies on resale prices, this would mute the effects of changes in resale value on new vehicle demand.

This theory leaves two questions unresolved. First, since equilibrium resale price adjustments are central to the theory, how much do used EV subsidies actually affect resale prices? Second, what are the quantitative effects of EV subsidies in a full model with realistic policy details and empirical parameters? The rest of the paper tackles those questions.

4 Data

This section presents our data. Table 2 presents summary statistics, and Appendix C presents additional details.

Following the U.S. tax credit eligibility criteria, we define "electric vehicles" to include plug-in hybrids, and we define "gasoline vehicles" to include hybrids without plugs. Our analyses include all light-duty vehicles except sports cars, full-size vans, uncommon powertrains (fuel cell, biofuels, natural gas, etc.), and luxury brands with average new vehicle prices above $200,000.

To estimate the demand system for the structural model, we use a one-year cross section. Each model year's vehicles typically become available in the fall of the previous calendar year, so we use prices and transactions from October 2022 through September 2023 and refer to this as "2023." To simplify the choice set, we aggregate across models to what we call the "car type": each combination of brand, powertrain (gas-only, hybrid, plug-in hybrid, and electric-only), and class (car, SUV (including minivans), and truck). Thus, for example, one car type is Toyota plug-in hybrid SUVs. The choice set includes all integer ages from 0 (i.e., new) to 19. After grouping and dropping less-common choices, there are 1,616 car type-by-age observations in the demand estimation.

We purchased two nationwide vehicle registration datasets from Experian, both initially at the level of model year, model, powertrain, and owner type (e.g., individuals versus fleets). The first dataset contains the counts of vehicles registered at the ends of Q3 2022 and Q3 2023, i.e. the total *stock* of vehicles. The second dataset contains the counts of vehicles transacted in each month from January 2022 through March 2024, i.e. the monthly *flows* of vehicle transactions. We have separate counts of dealership versus private party transactions. The top panel of Table 2 shows that the average car type-age observation had an initial stock of 135,600 registrations at the end of Q3 2022 and an annual flow of 26,100 transactions from October 2022 to September 2023.

We have confidential transaction-level microdata from dealerships covering January 2022 through December 2025 through a research partnership with Cox Automotive. This confidential dataset initially includes 38 million observations and provides a unique opportunity for academic research. The Cox data include 34 and 31 percent of the nationwide new and used dealership transactions reported in the Experian data. We observe the week of the transaction, VIN, lease terms, transaction price (excluding taxes, fees, and aftermarket charges), rebate amounts, mileage, dealership identifier, state, and buyer zip code. Our "price" variable is the reported transaction price net of any rebate; we ensure that this is gross of any EV tax credit.

To clean the Cox data, we drop leases, the highest and lowest 1/2 percent of observations for price, and the highest 1/2 percent for mileage. For the reduced-form estimates in Section 5, we include only used vehicles aged two and older (thus satisfying the IRA used EV tax credit eligibility requirement) and model years 2011 and later (since 2011 is the earliest EV model year in our data), giving a dataset of

Table 2: **Summary Statistics**

	(1) Mean	(2) Std. dev.	(3) Min.	(4) Max.	(5) Obs.
Panel (a): 2023 Experian Registrations and Transactions					
Initial stock (000s)	135.6	176.5	0.243	910.5	1,616
Transactions (000s)	26.1	54.7	0.032	742.0	1,616
Panel (b): 2022–2025 Cox Transactions					
Price ($000s)	27.3	14.7	0.002	480.0	16,389,144
2023 average price ($000s)	21.9	16.8	2.51	131.2	1,616
Panel (c): 2023 National Vehicle Experience Survey					
EV first choice	0.091	0.333	0	1	165,398
EV second choice	0.106	0.352	0	1	69,600
Household income ($000s)	167.7	193.9	10	1000	130,836
Panel (d): 2022 NHTS (Vehicles Purchased in Last 12 Months)					
Household income ($000s)	110.6	86.0	5	300	1,557
Model year	2,015	7.27	1,982	2,023	1,557
Panel (e): 2009 NHTS (All Vehicles)					
Months since purchase	55.2	46.8	1	228	265,807
Model year	2,000	6.52	1,974	2,010	265,807

The two rows of Panel (a) present counts of registrations at the end of Q3 2022 and transactions from October 2022 to September 2023. This uses data collapsed to "car type" (brand, powertrain, and class) by age for use in the demand estimation in Section 6. The two rows of Panel (b) present transaction prices for used EVs and GVs for the bunching estimator in Section 5 and average prices by car type and age for the demand estimation. Panel (c) presents data from the National Vehicle Experience Survey. Panels (d) and (e) present data from the National Household Travel Survey (NHTS).

16,389,144 used EV and GV transactions. Panel (b) of Table 2 shows that the average transaction in the cleaned reduced-form dataset had a price of $27,300, and the average car type-by-age combination used for demand estimation had a price of $21,900.

The structural model uses microdata from two consumer surveys. First, we have confidential microdata from the 2023 National Vehicle Experience Survey (NVES), a nationally representative survey of new vehicle buyers carried out by the market research firm Strategic Vision. We observe the model purchased, buyer income and sample weight, whether the buyer considered any other vehicles, and if so, the model of the other vehicle most seriously considered—i.e., the "second choice." Panel (c) of Table 2 shows that 9.1

percent of vehicles purchased in the NVES data were EVs, 10.6 percent of second choices were EVs, and the average buyer's household income was $167,700.

Second, we use public data from the National Household Travel Surveys (NHTS) from both 2022 and 2009. The 2022 NHTS data do not include purchase date for vehicles bought more than one year before, so we must limit our sample to vehicles bought in the last year. The 2009 NHTS data include month of purchase for all vehicles regardless of when purchased.

5 Bunching Estimator: Effects of Used EV Tax Credits on Resale Prices

As described in Section 2, the IRA used EV tax credit began in January 2023 and was available for transactions priced at $25,000 or less. Dealership transfer began in January 2024; this allowed buyers to benefit at the time of purchase (instead of on the next year's tax payment) and eliminated the need for the buyer to have tax liability. The tax credit ended on September 30, 2025. This section uses a bunching estimator to estimate the effect of these tax credits on used EV prices, both before and after dealership transfer.

5.1 Descriptive Figures

We first present descriptive evidence on bunching below the $25,000 price limit. Figure 1 presents the distributions of transaction prices for used vehicles that were at least two years old (e.g., model year 2021 and earlier for the 2023 distribution) and were thus potentially eligible for the tax credit. We superimpose the distributions from 2022, 2023, and January 2024 through the expiration in September 2025, which we label as "2024+." Each bar is a bin from $[x],001 to $[x+1],000.

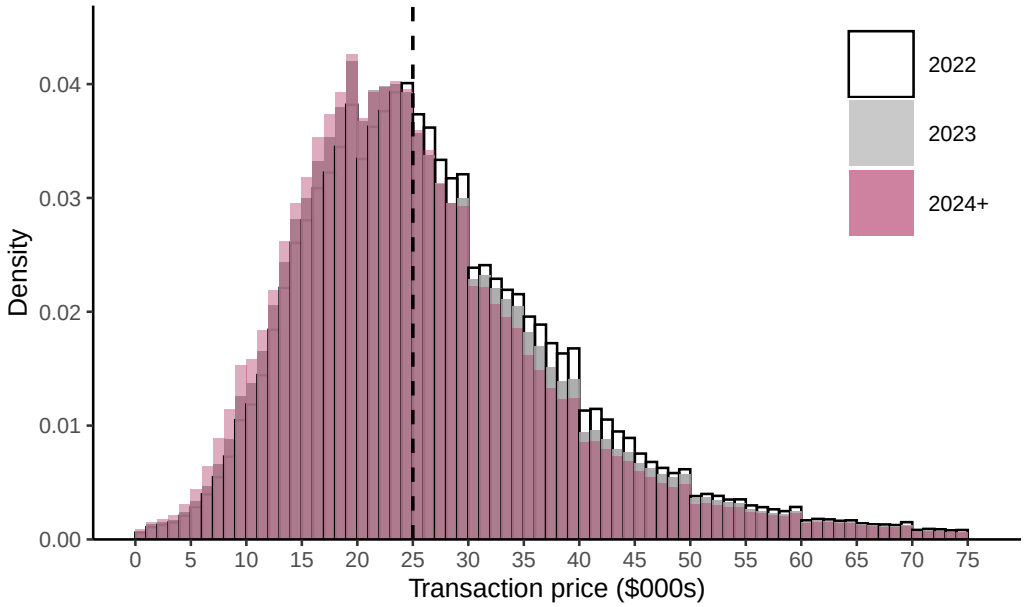
Panel (a) shows that the gas vehicle price distributions for all years are fairly smooth except for "left-digit effects": bunching just below round numbers that are multiples of $5,000 and $10,000. Panel (b) presents the electric vehicle price distributions. Left-digit effects are again clearly visible. In 2022, before the tax credit took effect, there was no bunching of used EV prices below $25,000. In 2023, the tax credit's first year, the grey bars show some excess mass just below $25,000. In 2024+, when dealership transfer was possible, the maroon bars show substantial excess mass below $25,000.

Our bunching estimator will identify the upward price shift from the tax credit that is consistent with the observed amount of excess mass. Intuitively, the more the tax credit shifts prices upward, the more excess mass we will observe at the price limit.

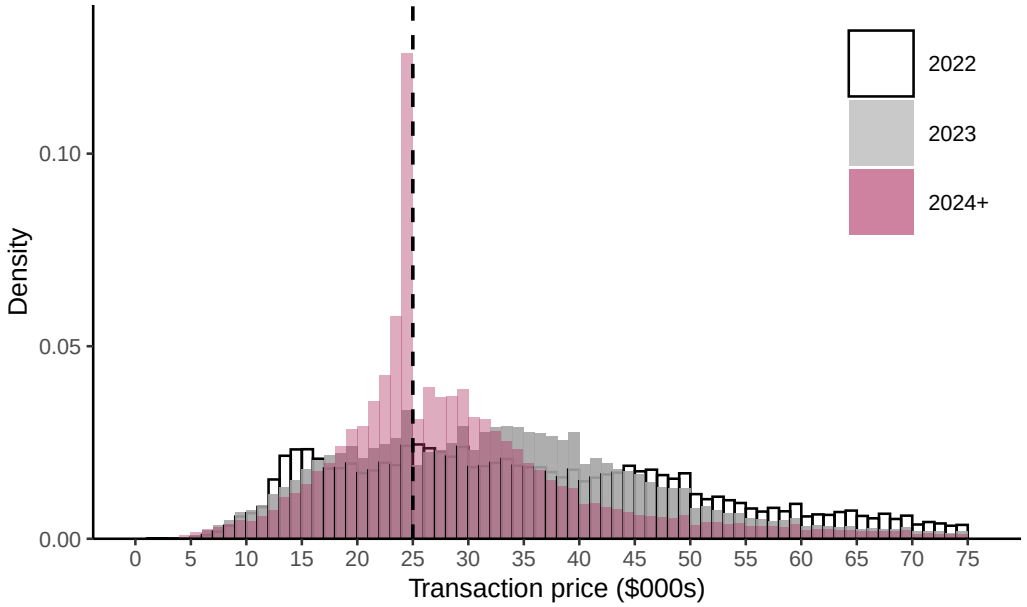
Figure 1 shows three factors that our bunching estimator needs to account for. First, left-digit effects could generate at least some excess mass just below $25,000 even without the tax credit. Second, the 2024+ distribution shows excess mass not just in the bin from $24,001 to $25,000, but also in the bin from $23,001 to $24,000. This could arise if dealerships post initial offer prices closer to $25,000, but buyers then negotiate downward. As a result, there is a wider "bunching region" where excess mass might arise. Third,

Figure 1: **Used Vehicle Transaction Price Distributions**

(a) Gasoline Vehicles



(b) Electric Vehicles



Notes: This figure presents the distributions of used vehicle transaction prices in the Cox Automotive dealership data in 2022, 2023, and January 2024–September 2025 (labeled "2024+"). Panels (a) and (b), respectively, present the distributions for gas vehicles and electric vehicles. The dashed vertical line is at $25,000, the transaction price limit for the used EV tax credit. Each bar is a bin from $[x],001 to $[x+1],000. The distributions are truncated at $75,000.

there may be a small amount of missing mass just *above* $25,000 in both 2023 and 2024+. This could arise if dealerships drop the price of vehicles that would cost just above $25,000 to compete with credit-eligible vehicles and/or sell the vehicles faster. We call this "downward bunching."

5.2 Bunching Model

For the bunching estimator, we informally think of the used vehicle market as a frictionless matching market between sellers of vehicles with heterogeneous quality and buyers with heterogeneous willingness-to-pay for quality. Left-digit effects change buyers' *perceived* prices, decreasing demand above round-number thresholds.

Let $T \in \{1, 0\}$ index the "with-subsidy" and "no-subsidy" counterfactual scenarios. Define $p_{iT} \sim F_T$ as the equilibrium price of vehicle i in scenario T, so p_{i1} is observed starting in 2023. Define $p^L_{iT} \sim L_T$ as the "latent price": the equilibrium price if there were no left-digit effects. Further define $f_T(p) := F'_T(p)$ and $l_T(p) := L'_T(p)$ as the respective probability density functions. We model actual prices as a transformation of latent prices: $f_T(p) = \Lambda(l_T(p))$, where the function $\Lambda(\cdot)$ shifts transaction prices near round numbers.

If the distributions of market primitives (vehicle quality and buyer WTP) are smooth, we can expect that the no-subsidy latent price density l_0 is also smooth. Formally, we assume that this density is approximated by an order-K polynomial:

$$l_0(p) = \sum_{k=0}^{K} \beta_k p^k. \tag{2}$$

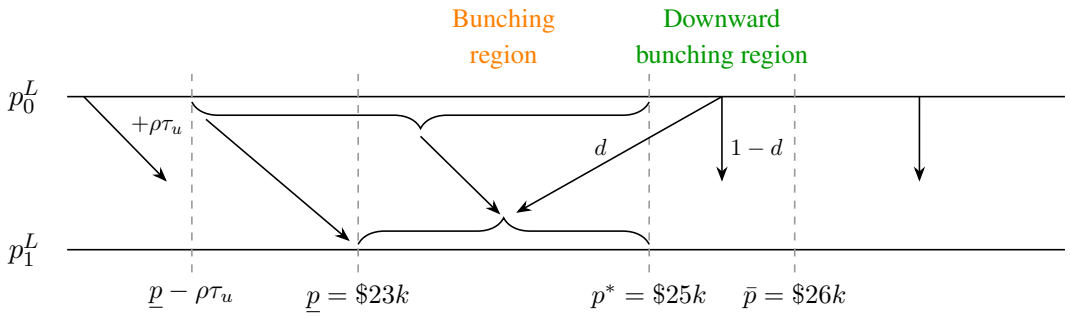
Consistent with the descriptive histograms above, our primary analyses assume that excess mass can arise anywhere in a "bunching region" from $\underline{p} = \$23{,}001$ to the transaction limit of $p^* = \$25{,}000$, and that "downward bunching" could occur for transactions that would be priced from $25,001 to $\overline{p} = \$26{,}000$. We model that the used EV tax credit τ_u has the following effects in four regions of the latent price distribution.

1. Latent prices p^L_0 below $\underline{p} - \rho\tau_u$ shift up by a constant amount $\rho\tau_u$, where ρ is a pass-through rate.
2. Latent prices p^L_0 between $\underline{p} - \rho\tau_u$ and p^* bunch somewhere in the bunching region between $\underline{p}$ and p^*.
3. Latent prices p^L_0 between p^* and $\overline{p}$ bunch downward to the bunching region with probability d, and are unaffected with probability $1 - d$.
4. Latent prices above $\overline{p}$ are unaffected.

Appendix D.1 states these more formally, and Figure 2 provides a graphical illustration.

Since prices above $\overline{p}$ are unaffected and prices below $\underline{p}$ have shifted up by a constant amount $\rho\tau_u$, the mass of transactions in L_1 between $\underline{p}$ and $\overline{p}$ must equal the mass in L_0 between $\underline{p} - \rho\tau_u$ and $\overline{p}$:

Figure 2: **Illustration of Price Shift Assumptions**



Notes: This figure presents the assumed latent price shifts from the no-subsidy counterfactual (top of figure) to the with-subsidy counterfactual (bottom of figure).

$$L_1(\bar{p}) - L_1(\underline{p}) = L_0(\bar{p}) - L_0(\underline{p} - \rho\tau_u). \tag{3}$$

We call this "mass equivalence."

5.3 Bunching Estimation Strategy

We observe f_1, the equilibrium prices with EV tax credits. Our goal is to predict f_0, the equilibrium prices without EV tax credits. Our empirical strategy goes from f_1 to f_0 in three steps:

1. estimate left-digit effects $f_T = \Lambda(l_T)$ and predict the latent with-subsidy density $l_1 = \Lambda^{-1}(f_1)$;
2. jointly estimate the no-subsidy latent density l_0 and price shift $\rho\tau_u$;
3. predict the no-subsidy density $f_0 = \Lambda(l_0)$.

Appendix D.2 presents full details. In this section, we focus on the intuition for step 2.

In step 2, we find the value of the upward price shift $\rho\tau_u$ that explains the amount of excess mass in the latent with-subsidy price distribution l_1. Intuitively, if there is a lot of excess mass at the transaction price cap, the tax credit must have shifted prices up by a large amount. More precisely, we search for the $\rho\tau_u$ that satisfies the mass equivalence constraint (per equation (3)) under the smoothness assumption (per equation (2)).

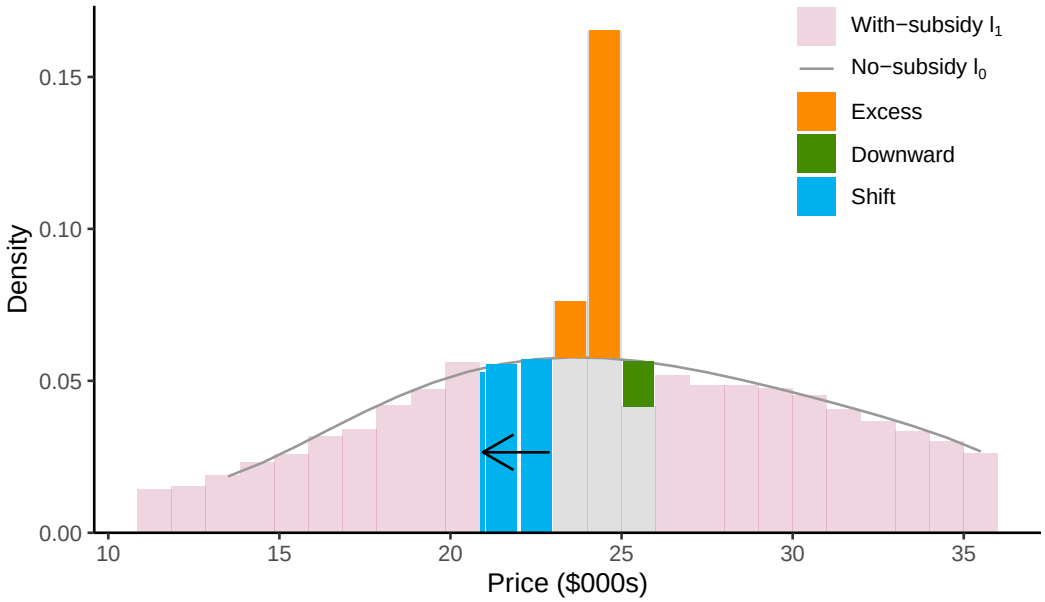
Figure 3 illustrates the approach, using data from January 2024 to September 2025 and our eventual empirical estimate of $\widehat{\rho\tau_u} \approx \$2{,}150$. Above \$26,000, the maroon bars are the with-subsidy latent density l_1—i.e., the observed price distribution after undoing left-digit effects. Below \$23,000, the maroon bars are also l_1, except shifted to the left by $\widehat{\rho\tau_u} \approx \$2{,}150$. The gray curve is a 5th-order polynomial fit of $\hat{l}_0$. The green area is the missing mass just above \$25,000 relative to the smooth polynomial fit—i.e., the

amount of downward bunching. The orange area is the excess mass in the bunching region (from $23,001 to $25,000), relative to the polynomial fit. The blue area is orange minus green—i.e., the amount of excess mass attributable to the upward price shift, disciplined by the smooth polynomial fit.

$\rho\tau_u$ is point identified. At the estimated $\rho\tau_u$, the blue area of width $\rho\tau_u$ equals exactly orange minus green. At a candidate price shift $\rho\tau_u$ that is too small (or too large) to satisfy mass equivalence, there is not enough (or too much) blue compared to orange minus green.

We use bootstrapped standard errors, following Kleven and Waseem (2013).

Figure 3: **Using Bunching to Identify the Incidence of Used EV Tax Credits**



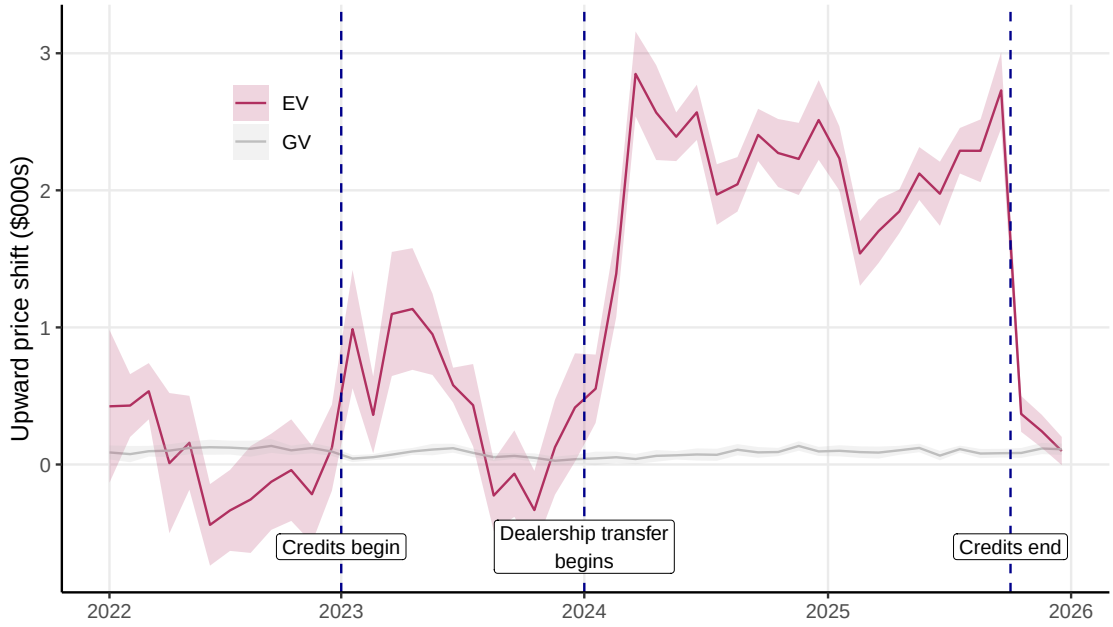
Notes: This figure illustrates the bunching estimator identification. See text for details.

5.4 Bunching Results

Price shift estimates. Figure 4 presents the estimated upward price shift $\widehat{\rho\tau_u}$ for each month of the sample, separately by powertrain. For electric vehicles, the descriptive histograms in Figure 1 had shown only limited excess mass in 2023, and significant excess mass in January 2024–September 2025. Consistent with that, Figure 4 shows that the estimated price shift $\widehat{\rho\tau_u}$ averaged a few hundred dollars in 2023 but jumped substantially within the first three months of 2024.[13] The speed of this change suggests that it was caused by a discrete event at the beginning of 2024—presumably dealership transfer—instead of more gradual trends

[13] We are not aware of an economic reason why the estimates are statistically different across months in 2023, but there are only a few thousand used EV transactions observed each month, and each month's $\widehat{\rho\tau_u}$ estimate seems to be visually consistent with its excess mass shown in Appendix Figure A4.

Figure 4: **Resale Price Shift by Month**



Notes: This figure presents the month-specific estimates of the upward price shift $\widehat{\rho\tau_u}$ from the used EV tax credit.

such as general consumer awareness of the tax credit. As expected, the estimated $\widehat{\rho\tau_u}$ dropped to effectively zero after the tax credit ended in October 2025.

For gas vehicles, the descriptive histograms in Figure 1 had shown no material excess mass of prices below $25,000. Consistent with that, Figure 4 shows price shifts that are close to zero (averaging $90) and much smaller than the EV price shift in 2024+. The fact that the GV estimate is not exactly zero could be explained by imperfect polynomial fits to l_0 or additional left digit bias at $25,000 beyond our estimated correction Λ.

Panel (a) of Table 3 presents estimates of $\widehat{\rho\tau_u}$ by period: 2022, 2023, and 2024+. As expected, the GV estimates are close to zero, as are the EV estimates for 2022. For EVs in 2023 and 2024+, we estimate upward price shifts of $406 and $2,154, respectively. Dividing by the $\tau_u = \$4{,}000$ gives estimated pass-through rates $\hat{\rho}$ of about 10 percent and 54 percent, respectively. In other words, the EV tax credit had very limited effects on the market in 2023, and much larger effects after dealership transfer began in 2024.

Robustness checks and threats to identification. These estimates do not change substantively in a variety of different alternative specifications presented in Appendix D.3, including alternative polynomial orders K and assumptions on the bunching region $\underline{p}$ and downward bunching limit $\overline{p}$. In that appendix, we find no evidence of bunching in average APRs. Such bunching would not undermine the identification strategy, but would suggest that some of the apparent price reduction was recouped through financing terms, allowing

lenders or dealers to capture some of the incidence of the credit.

The key identifying assumption is the smoothness assumption in equation (2). One important strength of the bunching estimator relative to a difference-in-differences (DiD) approach to estimating pass-through is that smoothness is more plausible than the parallel trends assumption required for DiD. For example, Figure 1 showed that the distribution of used vehicle prices shifted downward in 2023 and 2024+ as COVID-related supply shortages eased. Such changes in market conditions could bias a DiD estimator but do not bias our bunching estimator as long as they are continuous around $25,000. One threat to the smoothness assumption would be if more price-eligible used EVs were sold through dealerships instead of by private parties; this would increase the mass of transactions at all prices below $25,000. Appendix D.4 finds no evidence of this.

Economic implications. Are the estimated price shifts large or small? And can the increased effect in 2024 be fully explained by the fact that dealership transfer eliminated the requirement that buyers have income tax liability? Proposition 5 in Appendix B.8 derives the theoretically expected upward price shift for lower-quality EVs below the transaction price limit. In a short-run response to a surprise subsidy, the quantity of used EVs is fixed. During this period, used EVs had low scrap rates, and new EV tax credits also became more generous, so we assume fully inelastic scrappage and no net new-used substitution ($g' = 0, D_c' = 0$). Under those assumptions, the proposition predicts an upward price shift of $\Delta p_{ut} = \mu\tau_u$, where μ is the share of buyers that are eligible for the credit.

In Appendix D.5, we use NVES and IRS data to estimate the average share of a $4,000 subsidy that could be claimed by those purchasing vehicles costing under $25,000—specifically whether they have income below Section 25E limits and tax liability. This gives $\mu \approx 0.49$ for 2023, and $\mu \approx 0.76$ for 2024, and thus predicted price shifts of $1,970 in 2023 and $3,030 in 2024. Therefore, the 2023 estimated price shift is almost five times less than theory predicts. Furthermore, the estimated change from 2023 to 2024 is much more than predicted, both in dollar units and percent terms.

One potential explanation for this result is that dealership transfer increased "attention," broadly defined, by making the tax credit immediate, certain, and salient to buyers. Furthermore, the increase in potential appeal to buyers and/or required engagement from dealerships could have caused dealerships to more fully inform buyers about the tax credit. As noted in Section 3.4, the limited price shift in 2023 shifts the incidence to statutory recipients and would attenuate the equilibrium adjustments—including how resale price increases should boost new EV demand and thus generate environmental benefits. Put differently, the used EV tax credits might have had very limited environmental benefits were it not for dealership transfer. This connects to long-standing concerns mentioned in Section 2 about the lack of salience of energy tax credits, and underscores that the *delivery* of tax credits is crucial, not just the *amount*.

Under our price shift assumptions, we can do more than just estimate $\widehat{\rho\tau_u}$: we can simulate the full no-subsidy counterfactual price distribution and simulate the price effects in different regions. To do this,

we transform each observed with-subsidy price p_{i1} to a latent price p_{i1}^L, shift the latent prices according to assumptions described above, and re-apply left-digit effects to get the no-subsidy counterfactual prices p_{i0}; see Appendix D.6 for details. This analysis is interesting because it allows us to calculate the overall market-wide average price effect.

Panel (b) of Table 3 presents the modeled price effects for used EV transactions in four different regions of the observed price distribution F_1, for both 2023 and 2024+. For example, the table shows that for observed transaction prices from \$13,334 $\leq p_1 \leq$ \$23,000, the average modeled price increase for 2024+ is \$2,157. However, transactions in that price range were only 23.3 percent of the market for used EVs aged two and older. The bottom row shows that the overall average price effects were \$119 in 2023 and \$802 in 2024+. Naturally, these market-wide effects are much smaller than the \$4,000 subsidies given to eligible transactions.

The table quantifies an interesting economic effect of the transaction price limit: it induces some sellers in our downward bunching region (representing 4.1 percent of the market in 2024+) to reduce prices of vehicles that would otherwise sell for just over the price limit. This reduces overall average used EV prices and generates a transfer from sellers (who are on average richer) to buyers (who are on average poorer). The new EV tax credit under the IRA also had a price limit, and Tesla cut the price of one model in a way that allowed it to qualify (Domonoske 2023).

Given this empirical evidence for short-run equilibrium resale price adjustments (at least after dealership transfer), the next section models the market and welfare effects of EV subsidies in long-run equilibrium.

Table 3: **Resale Price Effects**

Panel (a): Estimated Upward Price Shift ($)

	(1) 2022	(2) 2023	(3) 2024+
GV	108	68	83
	(21)	(11)	(14)
EV	122	406	2,154
	(71)	(55)	(77)
EV (theoretical prediction)	0	1,966	3,029

Panel (b): Modeled Price Effects

Observed price range ($000s)	2023		2024+	
	Share of transactions	Average price effect ($)	Share of transactions	Average price effect ($)
[0, 13.3]	0.049	321	0.036	1,610
(13.3, 23]	0.202	406	0.233	2,157
(23, 26]	0.078	274	0.215	1,126
Upward shift ($23 < p_0 \leq 25$)	0.056	473	0.174	1,462
Downward bunching ($25 < p_0 \leq 26$)	0.022	-221	0.041	-314
26+	0.671	0	0.516	0
Total	1	119	1	802

Notes: Panel (a) presents estimates of $\widehat{\rho\tau_u}$ using the procedure described in Appendix D.2. The "theoretical prediction" row uses the Proposition 5 prediction that $\Delta p_u = \mu\tau_u$, where μ is our estimate of the share of buyers that are eligible for the tax credit. Panel (b) presents the modeled average price effects in different parts of the observed used EV transaction price distribution, using the procedure described in Appendix D.6. The $23–$26k range is broken down into two groups (one that shifted upward, a second that may have shifted downward) depending on the counterfactual no-subsidy price p_0.

6 Structural Model

Our structural model builds on the theoretical model in Section 3, but enriches the choice set and uses realistic empirical parameters. The upcoming subsections provide brief overviews of the setup, demand, market equilibrium, and externality calculation, respectively. Appendix E provides details.

Two considerations were important to our modeling decisions. First, while the theoretical insights were clearer in a stationary model, the actual vehicle market is evolving due to policy changes and new EV models. Thus, we want to consider both stationary and non-stationary equilibria. Second, an important

economic feature of the IRA used EV tax credit was that it was only available on the vehicle's first transfer. Thus, we want a model that tracks how long new car buyers hold vehicles before reselling and then identifies which available used EVs are on their first transfer. Existing models were not immediately suited to these needs: for example, Gillingham et al. (2023) assume a stationary equilibrium, and some other models don't explicitly track holding times and transfers (e.g., Bento et al. 2009; Jacobsen 2013; Jacobsen and van Benthem 2015).

6.1 Setup

Continuing and extending our earlier notation, i indexes consumer types, j indexes "car types" (aggregates by brand, powertrain, and class), and a, y, and t index vehicle ages, model years, and simulation years, respectively. In any given simulation year, age and model year are co-determined: $t \equiv y + a$.

Choice set. Within each car type j, the choice set of vehicles available for purchase can include each integer age $a \in \{0, 1, 2, ..., 19\}$.

Holding time and scrap decision. After buying a vehicle, each consumer holds the vehicle for an exogenous holding time of $H_i \in \{1, 2, ..., 20\}$ years. After those H_i years, consumers either scrap or resell their vehicle and then buy a different vehicle. Analogous to Section 3, vehicles that reach the end of their holding time at age 19 or younger receive a wear-and-tear draw ζ and can either be scrapped or reconditioned for resale. Vehicles that reach the end of their holding period at age 20 or older are all scrapped.

We allow the scrap rate $g_{ja}(p_{jat})$ to vary by car type and age, and we assume that the distribution of wear-and-tear draws ($\zeta \sim G$) is such that $g_{ja}(p_{jat})$ is isoelastic. We assume that the scrap elasticity is -0.7, following the empirical estimate from Jacobsen and van Benthem (2015). We then estimate scrap rate level shifters for each car type and age using the Experian data. We assume scrap values $v_j^s = \$1000$ for EVs and $v_j^s = \$500$ for GVs. Appendix E.1 provides details.

Credit eligibility. We allow consumer type i's credit eligibility e_{ia} to depend on vehicle age a, as income limits can differ between the new and used EV subsidies. In any given year, it may be that some individual used EVs available for sale are on their first transfer (and thus eligible for the tax credit), and some are not. We refer to individual vehicles within a car type as "VINs," in reference to their 17-digit Vehicle Identification Number. Eligible VINs sell at an additional "eligibility premium" p_{jyt}^e, which in equilibrium will be in the range $0 \leq p_{jyt}^e \leq \tau_{jyt}$. We set $p_{jyt}^e = 0$ for all jyt where all VINs are eligible, including all used EVs aged two or more in the policy's first year and all new EVs. We assume frictionless matching between eligible consumers and eligible VINs. Thus, for a given jyt, eligible consumers will always pay $\tau_{jyt} - p_{jyt}^e$ less (after the tax credit) than ineligible consumers.

New vehicle supply. Our simulations in the body of the paper assume that all new vehicles and the numeraire are supplied in perfect competition, with constant price equal to marginal cost. We make this assumption for two reasons. First, a constant subsidy-exclusive new vehicle price is consistent with empirical estimates from Sallee (2011), Gulati, McAusland, and Sallee (2017), and Allcott et al. (2024), while pass-through in a logit model with Nash-Bertrand supply is governed by functional form assumptions that may not be realistic (Weyl and Fabinger 2013; Miravete, Seim, and Thurk 2023). Second, welfare effects under imperfect competition depend on the assumed markup on the numeraire, which is contested and beside the point of our paper (De Loecker, Eeckhout, and Unger 2020; Benkard, Miller, and Yurukoglu 2026). Appendix F.1 presents simulation results with new vehicle marginal costs inferred from a Nash-Bertrand pricing assumption, as in Berry, Levinsohn, and Pakes (1995).

6.2 Demand

Demand model. We use a logit model with random coefficients, extended to accommodate resale markets and heterogeneous holding periods. Define $\boldsymbol{X}_{j,a+h}$ as a vector of observed vehicle characteristics, which can vary over years h of a consumer's holding period. Further define δ_{jy} as a vehicle's vertical quality and ε_{ijy} as a logit taste shock, which is constant across h. Consumer i's utility from buying car type j of age a and model year y in year t and holding for H_i years is

$$U_{ijyt} = -\alpha_i^p \underbrace{\left(p_{jyt} + e_{ia} \cdot \left(p_{jyt}^e - \tau_{jyt}\right) - \tilde{v}_{jy,t+H_i}\right)}_{\text{net-of-subsidy rent}} + \sum_{h=0}^{H_i-1} \underbrace{\left(\boldsymbol{\alpha}_i^X \boldsymbol{X}_{j,a+h} + \delta_{jy} + \varepsilon_{ijat}\right)}_{\text{annual non-price utility}}. \tag{4}$$

We assume that preferences across ages a within a car type j follow a vertical pure characteristics model, where $\varepsilon_{ijyt} = \omega_{ij} + \epsilon_{ijy}/\mu_\epsilon$, with $\mu_\epsilon \to \infty$. In the limit, this implies that no consumers have an idiosyncratic horizontal logit shock that could lead them to prefer an older model year to a newer one at the same price. Following Berry and Pakes (2007), we implement the pure characteristics model via nested logit, setting $\mu_\epsilon = 5$.

We want to have flexible, data-driven substitution patterns governing the three key directions in which consumers substitute in response to new and used EV subsidies: EVs versus GVs, new versus used vehicles, and younger versus older used vehicles. Thus, we define the observed characteristics $\boldsymbol{X}_{j,a+h}$ to be an EV indicator, a new vehicle indicator, and vehicle age in years. We then let the three preference parameters $\boldsymbol{\alpha}_i^X$ differ for consumers with household income over \$150,000 and also according to a random coefficient vector $\boldsymbol{\nu}_i$.

Demand estimation and results. Our demand estimation routine is broadly analogous to Berry, Levinsohn, and Pakes (2004). We identify the high-income preference shifters using NVES and 2022 NHTS microdata. We identify the random coefficient dispersions using the NVES second choice data and 2009

NHTS data on households with multiple vehicles. We back out the distribution of holding times H_i from the 2009 NHTS. We identify price elasticity by matching Grieco, Murry, and Yurukoglu (2024)'s estimated average firm-level price elasticity. We use tax credit amounts τ_{jyt} consistent with IRA rules as of January 2023, and we approximate IRA eligibility e_{ia} by assuming that consumers with household income under \$300,000 and \$150,000 per year are eligible for the new and used EV tax credits, respectively. Appendix E.2.1 provides demand estimation details.

Table 4 summarizes the demand estimation results by presenting key elasticities. The average own-price elasticity for new car types is -5.14, which as expected is somewhat more than the average firm-level elasticity of -4.69 that was targeted in the estimation. The aggregate new vehicle price elasticity is -0.86, which is in the range of the estimates in Grieco, Murry, and Yurukoglu (2024) and Allcott et al. (2026). The aggregate price elasticity of demand for new EVs is -1.48, which as expected is less elastic than the estimate of -2.1 for low and middle-income buyers in Muehlegger and Rapson (2022).

The diversion ratios across ages and powertrains govern the effects and optimal levels of new and used EV subsidies. When new EV rents rise or fall, 70 percent of the diversion is with new GVs, against 11 percent with used EVs. When used EV rents rise or fall, 61 percent of the diversion is with used GVs, against 34 percent with new EVs.

The across-powertrain substitution means that EV subsidies generate environmental benefits by displacing GVs, but the within-powertrain substitution means that new EV subsidies also increase EV scrappage and the total manufacturing externality, as discussed in Proposition 3. The bottom two rows show that the pure characteristics model delivers substantial substitutability between ages of the same car type. For example, when we individually raise the price of each car type of age 7 (holding constant prices of other ages), on average 79 percent of the diversion is to other ages of that same car type.

For our counterfactual simulations, we assume that the distribution of consumer preferences and holding times does not change in future years, with two exceptions. First, in our stationary simulations, we increase the demand shifters for all EVs so that EVs represent approximately 10 percent of new vehicle sales. Second, in our non-stationary simulations, we linearly increase the EV demand shifters over time so that EVs represent approximately 75 percent of new vehicle sales in 2058 (the final simulation year).

Fleet sales. In our cleaned Experian data, fleet buyers such as rental car companies and motor pools buy about 2.5 million new light-duty vehicles per year, most of which are eventually resold to individual consumers. Appendix E.3.2 describes how we construct fleet sale quantities from the Experian data. We assume that fleet sale quantities are exogenous and that purchases by fleets are not eligible for EV tax credits. However, we assume that resales from fleets to individuals are all first transfers, so individual buyers of fleet vehicles are potentially eligible to receive used EV tax credits.

Table 4: **Selected Elasticities**

Parameter	Estimate
Average new car type price elasticity	-5.24
Average firm-level price elasticity (Ford, GM, Toyota, Volkswagen, Hyundai)	-4.69
Aggregate new vehicle price elasticity	-0.90
Aggregate new EV price elasticity	-1.96
Aggregate (new+old) EV price elasticity	-1.59
New EV $\rightarrow$ new GV diversion ratio	0.57
New EV $\rightarrow$ used EV diversion ratio	0.16
Used EV $\rightarrow$ used GV diversion ratio	0.54
Used EV $\rightarrow$ new EV diversion ratio	0.41
New car type $\rightarrow$ used ages average diversion ratio	0.12
Age 7 car type $\rightarrow$ other used ages average diversion ratio	0.79

Notes: This table presents key elasticities implied by our demand estimates. To construct the diversion ratios from new EVs and used EVs, we simulate the effects of raising the price of all new EVs (or used EVs) simultaneously. To construct the diversion ratios from new car types and age 7 car types, we simulate the effects of raising the price of each new (or age 7) car type individually, holding all other prices constant, and report the average diversion ratio across car types, weighting by market shares.

6.3 Market Equilibrium and Welfare

An equilibrium is a vector of prices and eligibility premia $\{\boldsymbol{p}_t, \boldsymbol{p}_t^e\}$ for all years t such that

1. consumers correctly forecast vehicle prices: $\tilde{\boldsymbol{p}}_t = \boldsymbol{p}_t, \tilde{\boldsymbol{p}_t^e} = \boldsymbol{p}_t^e, \forall t$;
2. used vehicle markets clear (i.e., prices adjust so that supply equals demand for each car type and age), following equation (125) in Appendix E.3.1; and
3. markets for eligible VINs clear (i.e., eligibility premia adjust so that supply equals demand for credit-eligible VINs), following equation (127) in Appendix E.3.1.

We find stationary equilibria by iterating over beliefs, prices, and demand until convergence. For the non-stationary equilibria, we assume that starting in 2059, vehicle prices $\boldsymbol{p}_t$ take their stationary equilibrium values with no tax credits. We then forward simulate over the 35 years from 2024 to 2058, again iterating over beliefs, prices, and demand until convergence. Appendix E.4 provides equilibrium simulation details.

Total surplus is the sum of consumer surplus (including fleets) and negative externality reduction net of government spending. In non-stationary equilibria, we account for windfall gains or losses to consumers and fleets when unexpected subsidies change the resale prices of vehicles they own. As a stylized benchmark for

distributional concerns, we simulate "welfare-weighted" surplus with welfare weights inversely proportional to income, maintaining a population average weight of 1. Appendix E.5 provides welfare calculation details.

6.4 Externalities

We assume that vehicles impose four types of externalities: (i) CO_2 emissions from manufacturing, (ii) CO_2 and local air pollution from driving, (iii) accidents, and (iv) energy pricing externalities from gas taxes and residential electricity markups. We measure externalities by car type and model year, generally following Allcott et al. (2024). Appendix E.6 provides details.

We inflate all dollar values to July 2023 dollars. We assume a $241 per metric ton social cost of carbon (US EPA 2023) and a $13.2 million value of statistical life (VSL) (US Department of Transportation 2024). We assume that all vehicles are driven 10,529 miles per year, the national average reported in NHTSA (2022). We assume that mileage does not vary by vehicle age so that total mileage stays the same when consumers substitute between newer and older vehicles in counterfactual simulations.

Table 5 presents monetized negative externalities for average new electric versus gas vehicles. EVs have larger manufacturing CO_2 externalities than GVs: $2,807 versus $1,815. EVs also have larger accident externalities, because they weigh more. However, their driving CO2 emissions are lower, and their energy pricing externality is more positive. In total, EVs impose $1,108 in yearly negative externalities, against $1,522 from GVs. Our scrap rates imply an average vehicle lifetime of 16.3 years. Summing manufacturing and driving externalities over that expected lifetime, EVs and GVs impose total negative externalities of about $20,906 and $26,687, respectively.

These different externality magnitudes determine optimal EV subsidy levels through the logic of Proposition 3. On one extreme with fixed scrap rates, such that all diversion to new EVs is from GVs, the optimal corrective new EV subsidy would be the lifetime externality difference: $5,781. On the other extreme with fixed new + used EV demand, such that all diversion to new EVs is from used EVs, the optimal corrective policy would be a new EV *tax* equal to the EV manufacturing externality: $2,807. From the empirical diversion ratios presented above in Table 4, we know that reality is somewhere in between these two extremes. Appendix Figure A14 shows that externalities vary substantially across models, so heterogeneous vehicle-specific taxes would be more economically efficient.

Table 5: **Monetized Negative Externalities for New Gas and Electric Vehicles ($)**

Externality	(1) Gasoline vehicles	(2) Electric vehicles	(3) Difference
Manufacturing CO2	1,815	2,807	-992
Total yearly externalities	1,522	1,108	415
Driving local pollutants	27	40	-12
Driving CO2	986	501	485
Excess weight in accidents	764	980	-216
Energy pricing externality	-256	-413	158
Expected lifetime externality	26,687	20,906	5,781

Notes: This table presents average negative externalities by powertrain for new vehicles, weighting models by 2023 sales. Manufacturing CO_2 is a one-time cost in units of $, while the other categories are in $/year. The energy pricing externalities are positive fiscal externalities from gas taxes (for GVs) and positive residential electricity price markups (for EVs). Appendix E.6 provides details.

7 Counterfactual Simulations

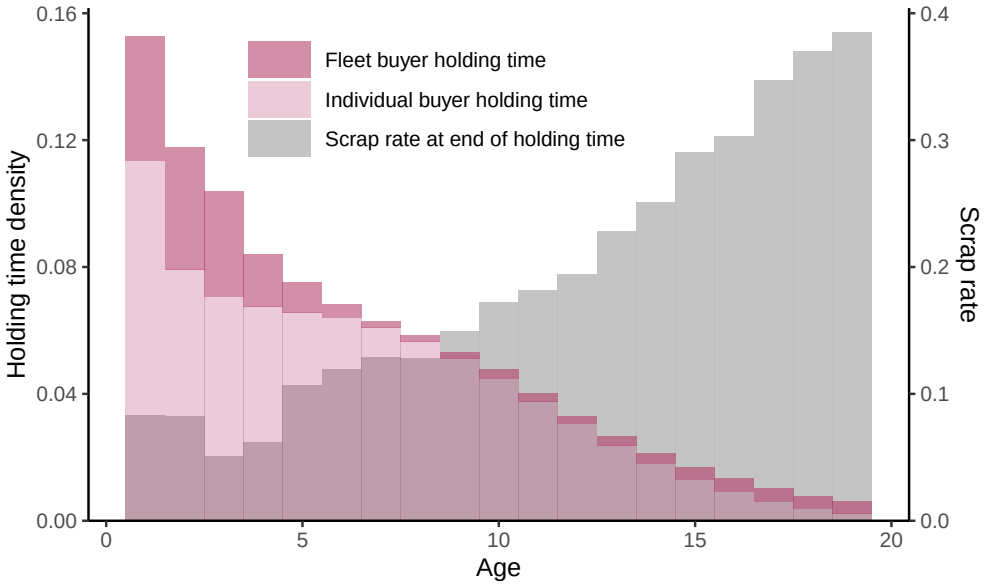
This section presents counterfactual simulations using the model described in Section 6. Section 7.1 presents simulations in stationary equilibrium, which connects directly to the theoretical results from Section 3. Section 7.2 presents simulations in non-stationary equilibrium, including a counterfactual that closely matches the Inflation Reduction Act's EV tax credits.

Modeled policies. Except in our final simulation designed to match the IRA, our simulations abstract away from the IRA's trade restrictions and allow all EV models to be eligible for new EV subsidies τ_n. Except in that final IRA simulation, we allow used EVs first transferred at age one to remain eligible for used EV subsidies on their first transfer at age two or older. (Under the IRA, used EVs first transferred at age one were not eligible for the used EV tax credit, which generates a small inefficiency in our model.)

Holding time and scrap rate. Before proceeding, Figure 5 presents data that explain many of our structural simulation results. The maroon bars are a histogram of holding times for new vehicles. The light maroon represents individual consumers buying new vehicles (derived from the 2009 NHTS as described in Appendix E.2.3), while the dark maroon represents fleets (as described in Appendix E.3.2). The gray bars present the scrap rate g for vehicles of each age that are at the end of their holding times and thus available

for resale (as described in Appendix E.1). This figure presents data for both EVs and GVs; scrap rates are similar between the two.

Figure 5: **New Vehicle Buyers' Holding Time and Scrap Rate**



Notes: This figure presents the distribution of new vehicle holding times as well as scrap rates by age. The maroon bars are a histogram of holding times for new vehicles. The light maroon represents individual consumers buying new vehicles (derived from the 2009 NHTS as described in Appendix E.2.3). The dark maroon represents fleets (as described in Appendix E.3.2). The gray bars present the scrap rate for vehicles of each age that are at the end of their holding times and thus available for resale (as described in Appendix E.1).

In both the IRA and our model, used EV tax credits are available for used EVs on their first transfer. The figure shows that about 78 percent of new vehicles are first resold in under 10 years. The scrap rate for ages 1–9 is relatively low (about 10 percent), while the scrap rate for ages 10–19 is much higher (about 27 percent).[14] Thus, credit-eligible used EVs have low scrap rates. Under our model's assumption of a constant-elasticity scrap function (and likely in reality), the scrap *derivative* g' with respect to resale price is thus also relatively low for credit-eligible used vehicles. Following the Proposition 1 equivalence result, the small scrap derivative g' for credit-eligible vehicles means that universal new and used EV subsidies will have similar effects, after adjusting for the survival rate $(1 - g)$. Moreover, the small scrap rate level g implies a minimal multiplicative survival adjustment $(1 - g)$ in that proposition. Our simulations will quantify exactly how "similar" the two subsidies are and illustrate the remaining differences.

[14] This scrap rate for vehicles conditional on being available for resale at the end of their holding periods is of course much higher than the unconditional scrap rate as a share of total stock.

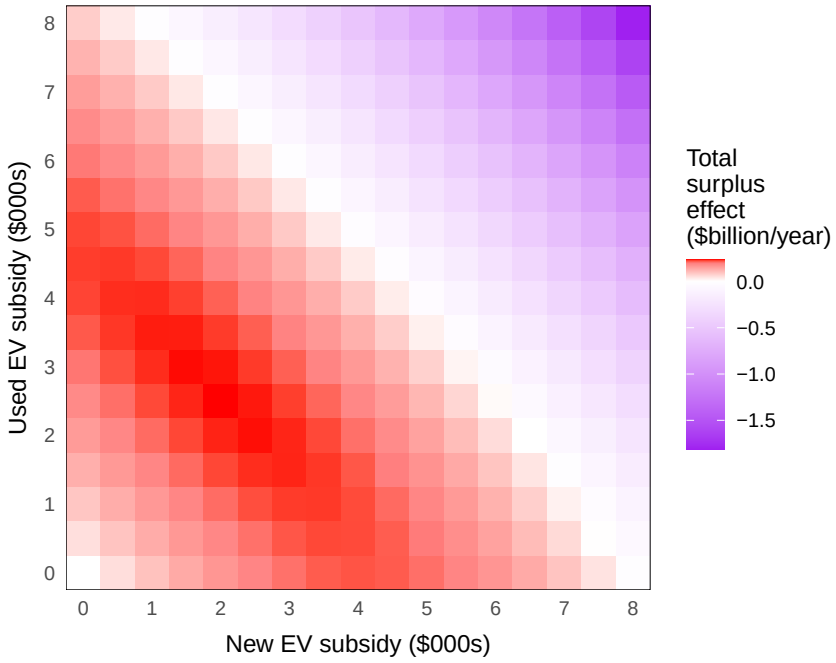
7.1 Stationary Equilibrium

Efficient subsidy levels. We begin by computing the total surplus effects of a range of different universal subsidy levels τ_n and τ_u, with all consumers receiving the same welfare weight $w_i = 1$. Figure 6 presents results. There are three takeaways. First, the downward-sloping level sets illustrate the Proposition 1 equivalence result, driven by the low scrap rate derivatives g' for credit-eligible (young) used EVs. The fact that the level sets have a slope of roughly -1 is driven by the low scrap rate levels g and thus minimal survival adjustment, so new and used subsidies of the same amount $\tau_n = \tau_u$ have similar effects.

Second, although the two subsidies have "similar" effects, there is a unique total surplus-maximizing pair of universal subsidies: $\{\tau_n^* \approx \$2,180, \tau_u^* \approx \$2,370\}$.

The third key takeaway is that the total surplus-maximizing sum of subsidies is $\tau_n^* + \tau_u^* \approx$ \$4,550, which is only about 79 percent of the \$5,781 lifetime externality difference between the average EV and the average GV. This follows from the logic of Proposition 3: as we document below, both new and used EV subsidies increase scrappage of older used EVs in addition to reducing GV use.

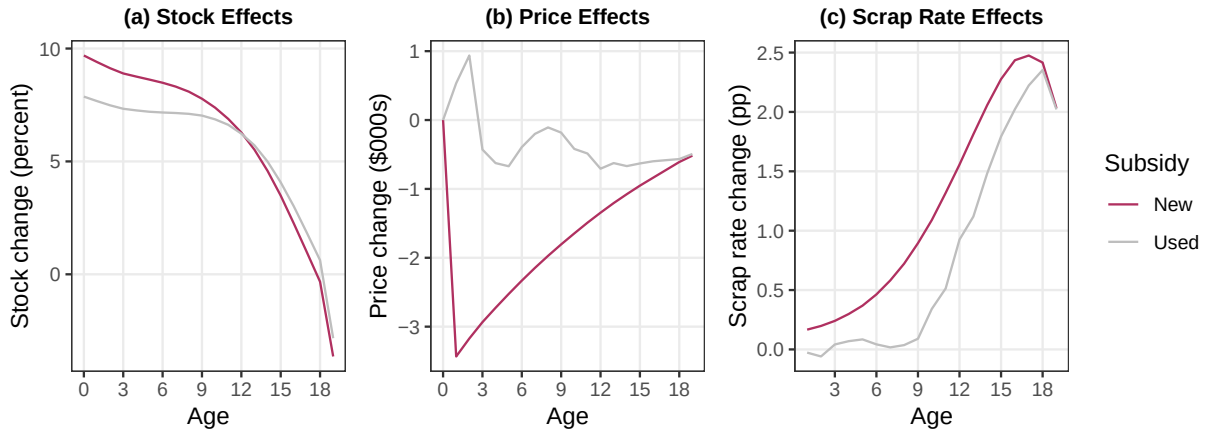
Figure 6: **Total Surplus Effects of New and Used EV Subsidies**



Notes: This figure presents total surplus changes relative to the zero-subsidy baseline across a grid of new and used EV subsidies in stationary equilibrium.

Market effects of \$4,000 subsidies. We now fix the subsidy amounts at \$4,000, a round number close to the optimal level, and compare new and used EV subsidies in more detail. Figure 7 presents effects

Figure 7: **Market Effects of EV Subsidies in Stationary Equilibrium**



Notes: These figures present the effects of $4,000 new or used EV subsidies on EV stocks, prices, and scrap rates in stationary equilibrium by age. Price effects are averages across consumers, weighting by baseline choice probabilities. Used subsidy versions are smoothed with a moving average.

of universal new and used EV subsidies on EV prices, stocks, and scrap rates in stationary equilibrium. The results extend the intuition developed in Section 3.2. New EV subsidies increase new EV sales and thus stocks of young used EVs (Panel (a)). This increased supply plus the demand shift toward new EVs decreases used EV prices at all ages (Panel (b)). This in turn increases scrap rates (Panel (c)), with larger percentage point effects on older vehicles. Used EV subsidies increase demand and thus prices for younger used EVs that are on their first transfer (left side of Panel (b)). The increased resale value increases new EV sales and thus stocks of young used EVs (Panel (a)). The shift in demand toward younger used EVs decreases prices of older used EVs that are not on their first transfer (right side of Panel (b)). Thus, scrap rates decrease slightly for young used EVs and increase substantially for older used EVs (Panel (c)).

Appendix Figure A15 presents parallel results for GVs. The effects are generally opposite-signed (since GVs are the substitute option) and smaller (since there are many more GVs on the road).

New and used EV subsidies with income and price limits. Table 6 presents more detailed comparisons of universal $4,000 new versus used EV subsidies in stationary equilibrium, as well as the implications of adding income and price limits. Columns 1–3 present new EV subsidies, while columns 4–6 present used EV subsidies. Columns 1 and 4 present universal subsidies (the same simulations as in Figure 7), columns 2 and 5 add symmetric $150,000/year income limits on each subsidy, and columns 3 and 6 have the income limits plus transaction price limits of $50,000 for new EVs and $25,000 for used EVs.[15] Panel (a) presents

[15] We use the same income limits for new and used EV subsidies to more clearly illustrate how income limits have different effects for each subsidy, per Proposition 4. When simulating price limits, to allow the model to converge, we simulate that the used EV subsidy decreases smoothly in a small range around $25,000 instead of dropping to zero immediately at $25,000.

market equilibrium outcomes, while Panel (b) presents welfare effects, all relative to a baseline with zero subsidies.

The table has six key takeaways. First, echoing Proposition 1, comparing columns 1 and 4 shows that universal new and used EV subsidies are close to equivalent in stationary equilibrium. Panel (a) shows similar effects on average rents, and Panel (b) shows similar effects on consumer surplus, externalities, and total surplus, as well as similar MVPFs. However, the different scrappage effects shown in Figure 7 generate some differences between the two subsidies, including a slight "flypaper effect," where τ_n reduces new EV rents more than τ_u does.

Second, all subsidy designs in columns 1–6 accelerate scrappage, especially the new EV subsidies. Columns 1 and 4 of Panel (a) show that universal new and used EV subsidies decrease average EV lifetimes by 0.52 and 0.35 years, respectively. In column 1, universal new EV subsidies increase new EV sales by 8.33 percent but increase total (new + used) EV stocks by only 5.23 percent. Thus, new EV subsidies decrease GV usage (and the corresponding negative externalities) by only 5.23/8.33 $\approx$ 63 percent as much as predicted by the new EV sales increase, with the remaining 37 percent offset by accelerated scrappage. The offset is smaller for used EV subsidies in column 4: they decrease GV usage by 4.76/6.78 $\approx$ 70 percent as much as predicted by the new EV sales increase, so 30 percent is offset by accelerated scrappage. This scrappage increase implies that more new vehicles must be made, increasing manufacturing CO2 externalities. We calculate that the \$4,000 new EV subsidy in column 1 reduces negative externalities by about \$3900 per additional new EV sold, which is consistent with the total surplus-maximizing subsidy amounts in Figure 6 and much less than the \$5,781 lifetime externality difference between EVs and GVs calculated in Section 6.4.

Third, if all consumers have equal welfare weights, the marginal value of public funds (MVPF) is close to one in all columns. In other words, EV subsidies generate only around \$1 of consumer surplus and negative externality reduction for every \$1 of net government spending. Column 1 shows that the MVPF of universal new EV subsidies is 1.04. This is lower than estimates in two other recent papers by Allcott et al. (2024) and Hahn et al. (2026). One key difference is that these papers do not endogenize scrappage, so they assume that additional EV sales only divert from GVs, not older EVs. This overstates the environmental benefits. In column 1, new EV subsidies generate only $382/4,483 \approx$ \$0.09of negative externality reduction per dollar of subsidy spending. Appendix Table A16 shows that if we (counterfactually) assume perfectly inelastic scrappage, new EV subsidies generate \$0.06 of negative externality reduction per dollar of subsidy spending, and the MVPF rises to 1.03.

Fourth, both new and used EV subsidies are regressive. New EV subsidies increase annual consumer surplus by an average of \$319 for consumers with household income above \$150,000, but only \$60 for consumers with household income below \$150,000. Despite their seemingly progressive *statutory* incidence, used EV subsidies are only slightly less regressive, increasing annual consumer surplus by \$284 for the

higher-income group, against only $56 for the lower-income group. This regressivity is driven by the fact that the higher-income group is 1.9 times more likely to buy EVs in the baseline stationary equilibrium. Welfare-weighting the MVPFs reduces them to 0.69 and 0.74 for new and used EV subsidies, respectively.

Fifth, the two subsidies diverge sharply when considering income limits: the income limit substantially increases the welfare-weighted MVPF for new EV subsidies, but not for used EV subsidies. This is driven by the mechanics of Proposition 4. New EV subsidies decrease used EV prices and thus increase subsidy-exclusive new EV rents, harming subsidy-ineligible higher-income people because they tend to buy new vehicles. By contrast, used EV subsidies increase used EV prices and thus decrease new EV rents, benefiting ineligible higher-income people.

Sixth, Columns 3 and 6 show that in the presence of income limits, transaction price limits *increase* regressivity of used EV subsidies. Since high-income people prefer expensive vehicles, one might intuitively think that limiting subsidies for expensive vehicles would be progressive. However, the IRA has transaction price limits *and* income limits. With income limits, adding transaction price limits is actually regressive, for a reason analogous to Proposition 4. Since the lower-income group does buy some higher-priced used EVs, subsidizing them increases their prices, harming high-income consumers because they are not subsidy-eligible. Transaction price limits undo this effect, removing the harm to high-income consumers. Price limits do increase the MVPF slightly, because higher-priced EVs tend to be larger and thus have more negative driving and accident externalities. Price limits thus are slightly closer to an optimal policy that differentiates across vehicles by their externalities.

Appendix Table A16 presents the simulated effects of new and used EV subsidies under alternative empirical moments and parameter assumptions. Increasing the substitutability between new and used vehicles reduces the MVPF by causing subsidies to further divert consumers away from older used EVs instead of GVs. Increasing the substitutability between EVs and GVs does the opposite, although even the substantial increase we consider only increases the MVPF to 1.04.

Alternative subsidy designs. Table 7 presents the effects of alternative subsidy designs, again relative to a baseline with no EV subsidies. The panel layout is the same as the previous table. Each column considers some optimal combination of new and used subsidy levels $\{\tau_n^*, \tau_u^*\}$ under an alternative policy design.

Column 1 presents the effects of the total surplus-maximizing subsidies of $\tau_n^* \approx \$2,180$ and $\tau_u^* \approx \$2,370$. Total surplus increases by $235 million per year, and the MVPF is 1.04.

The first key takeaway from both Figure 6 and Table 6 was that subsidizing *young* used EVs has broadly similar effects to subsidizing new EVs. This raises the question of whether subsidizing *older* EVs could restore the efficiency and distributional benefits theorized under Proposition 2. Column 2 explores this by limiting the used EV subsidy to EVs on their first transfer after age 10. We use the same subsidy amounts as column 1 to allow a direct comparison. Comparing columns 2 versus 1 shows that age 10

Table 6: **Effects of EV Subsidies in Stationary Equilibrium**

	New subsidy			Used subsidy		
	(1)	(2)	(3)	(4)	(5)	(6)
New EV subsidy ($000s)	4	4	4	0	0	0
Used EV subsidy ($000s)	0	0	0	4	4	4
Income limit ($000s)	–	150	150	–	150	150
Price limit ($000s)	–	–	50	–	–	25
Panel (a): Market Effects						
ΔAverage EV lifetime (years)	-0.52	-0.28	-0.16	-0.35	-0.37	-0.07
%ΔNew EV sales	8.33	3.98	1.56	6.78	6.83	2.07
%ΔNew + used EV stock	5.23	2.40	0.66	4.76	4.71	1.70
%ΔEV stock / %Δnew EV sales	0.63	0.60	0.42	0.70	0.69	0.82
ΔNew EV average rent ($000s/year)	-0.35	0.11	0.06	-0.30	-0.27	-0.05
ΔUsed EV average rent ($000s/year)	-0.24	-0.12	-0.04	-0.23	-0.14	-0.04
Panel (b): Welfare Relative to No Subsidy						
ΔConsumer surplus ($millions/year)	4,286	1,220	372	4,281	3,966	1,493
Inc ≥$150k: ΔCS ($/consumer-year)	319	-9	6	284	218	91
Inc <$150k: ΔCS ($/consumer-year)	60	48	13	56	65	23
ΔNegative externality ($millions/year)	-382	-195	-143	-359	-362	-266
Subsidy spending ($millions/year)	4,483	1,480	520	4,432	4,374	1,724
ΔTotal surplus ($millions/year)	185	-64	-5	208	-46	35
ΔWelfare-weighted total surplus ($millions/year)	-1,473	231	64	-1,238	-1,096	-406
MVPF	1.04	0.96	0.99	1.04	0.99	1.02
Welfare-weighted MVPF	0.69	1.14	1.11	0.74	0.76	0.78

Notes: This table presents the effects of new and used EV subsidies in stationary equilibrium relative to zero EV subsidies. Rents include subsidies for eligible consumers. Rent effects are averages across consumers, weighting by baseline choice probabilities. The marginal value of public funds (MVPF) is (ΔConsumer surplus − ΔNegative externality (excluding gas tax revenue))/(Subsidy spending − ΔGas tax revenue). The "welfare-weighted" total surplus and MVPF weight consumers by 1/income, holding constant the average consumer's weight.

eligibility substantially moderates the scrap rate effects, as evidenced by the near-zero reduction in average EV lifetime. This in turn slightly increases the MVPF, to 1.05.[16] Age 10 eligibility also makes the used EV

[16]With age 10 eligibility, a larger share of EVs will never receive the subsidy because they are never resold after age 10. This generates an allocative distortion where consumers prefer age 10 EVs over slightly younger models, reducing the efficiency benefits of delayed eligibility.

rent decrease as large as the new EV rent decrease, whereas the new EV rent decrease was much larger with age 2 eligibility. This increases progressivity and thus the welfare-weighted MVPF for age 10 eligibility.

Another key takeaway from Table 6 was that understanding scrappage is key for policy evaluation. Column 3 presents total surplus-maximizing subsidies under the (counterfactual) assumption that scrappage is fully inelastic. Since τ_u no longer has a scrappage-related efficiency benefit relative to τ_n, the optimal policy puts more weight on τ_n, with $\tau_n^* \approx \$5{,}310$ and $\tau_u^* \approx \$600$. The optimal sum of $\tau_n^* + \tau_u^*$ is much larger than in column 1, as are the total surplus gains. The difference between columns 3 versus 1 highlights the importance of scrappage and again underscores how a simplified model ignoring scrappage might overstate both optimal subsidy levels and net benefits.

Proposition 2 showed that given the flypaper effect plus higher-income people's stronger preferences for new EVs, the redistributive motive decreases the optimal τ_n^* more than τ_u^*. Column 4 explores this by presenting the new and used subsidies that maximize *welfare-weighted* total surplus, effectively adding a redistributive motive to the optimization. The optimal subsidies are now *taxes* of \$15,200 on new EVs and \$2,000 on used EVs. Comparing columns 4 versus 1 shows that consistent with Proposition 2, the redistributive motive decreases τ_n^* more than τ_u^*, although both decrease because even used EV subsidies are regressive. Consistent with the different optimization objective, (unweighted) total surplus drops substantially, while welfare-weighted total surplus increases substantially. Note that MVPFs below 1 are "better" for revenue-raising policies such as this one.

As we have seen, the IRA's EV transaction subsidies are inefficient in our model because they increase scrappage of older used EVs, which was already inefficiently high. An alternative design could be annual EV registration subsidies, which disincentivize scrappage of older used EVs regardless of whether they have been transacted before. Allowing a separate (and possibly negative) subsidy amount for new EV purchases could more precisely match the timing of EV externalities relative to GVs: a larger negative manufacturing externality ϕ_n plus a generally lower usage externality ϕ. Column 5 presents results at the optimal subsidy amounts: a new EV tax of \$1,140 and an annual registration subsidy of \$450 for used EVs. Panel (a) shows that new EV sales and EV lifetimes *both* increase. This is the first policy we have simulated that incentivizes new EV sales without accelerating scrappage. The MVPF and welfare-weighted MVPF increase to 1.05 and 0.79, respectively, and the annual total surplus gain rises to \$438 million, although the welfare-weighted total surplus effect becomes more negative.

As noted in Section 6.4, externalities vary substantially across vehicle models. This variation is strongly associated with weight, as heavier vehicles use more electricity and kill more people in accidents. Column 6 partially addresses this by allowing the new and yearly used EV subsidies in column 5 to each vary by vehicle class (cars, SUVs, and trucks). In that column, the optimal policy is new EV taxes of \$2,080, \$1,140, and \$4,000 and annual EV registration subsidies of \$690, \$380, and \$0 for cars, SUVs, and trucks, respectively. Class differentiation is the most beneficial policy so far, with an MVPF of 1.07 and total surplus gains of

$656 million per year.

Column 7 presents the model's social optimum, which is vehicle model-specific taxes that exactly equal the negative externalities from each new and used vehicle. This is a useful benchmark for comparing the effects of alternative policies on EV scrappage and other outcomes. The total surplus gains are $9.4 billion per year—more than 10 times larger than the class-specific annual subsidies in column 6. EV subsidies capture only a small share of the possible total surplus gains in the modeled optimum, because they do not affect the relative prices between gas vehicles, which represent most of the market.

Table 7: **Effects of Alternative Subsidy Designs in Stationary Equilibrium**

	Transaction subsidies				Annual subsidy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Age 10 eligibility	Inelastic scrappage	Welfare weights	EVs	EVs by class	Modeled social optimum
New EV subsidy ($000s)	2.18	2.18	5.31	-15.20	-1.14	(-2.08, -1.14, -4.00)	$-\phi_{nj} - \phi_j$
Used EV subsidy ($000s)	2.37	2.37	0.60	-2.00	0.45	(0.69, 0.38, 0.00)	$-\phi_j$
Income limit ($000s)	–	–	–	–	–	–	–
Price limit ($000s)	–	–	–	–	–	–	–
Panel (a): Market Statistics							
ΔAverage EV lifetime (years)	-0.48	-0.03	-0.34	1.68	0.22	0.25	0.26
%ΔNew EV sales	10.02	2.62	11.82	-30.37	10.63	10.90	10.20
%ΔNew + used EV stock	6.18	2.20	8.60	-20.68	10.94	11.32	10.75
ΔNew EV average rent ($000s/year)	-0.37	-0.11	-0.45	1.42	-0.44	-0.43	1.26
ΔUsed EV average rent ($000s/year)	-0.27	-0.11	-0.38	1.00	-0.35	-0.37	1.30
Panel (b): Welfare Relative to No Subsidy							
ΔConsumer surplus ($millions/year)	4,768	1,781	6,239	-14,416	8,360	8,570	-301,398
Inc ≥$150k: ΔCS ($/consumer-year)	332	115	446	-1,110	529	532	-7,815
Inc <$150k: ΔCS ($/consumer-year)	65	25	92	-191	123	129	-8,057
ΔNegative externality ($millions/year)	-457	-182	-693	1,485	-885	-1,334	-18,878
Subsidy spending ($millions/year)	4,990	1,863	6,586	-12,039	8,807	9,248	-291,982
ΔTotal surplus ($millions/year)	235	100	346	-3,862	438	656	9,462
ΔWelfare-weighted total surplus ($millions/year)	-1,451	-444	-1,820	2,144	-2,002	-1,684	13,883
MVPF	1.04	1.05	1.05	1.30	1.05	1.07	0.97
Welfare-weighted MVPF	0.73	0.77	0.74	0.84	0.79	0.83	0.95

Notes: This table presents the effects of alternative subsidy designs in stationary equilibrium relative to zero EV subsidies. Column 1 presents total surplus-maximizing new and used EV transaction subsidies. Column 2 matches column 1, except making used EVs eligible for the subsidy on their first transfer after age 10. Column 3 presents total surplus-maximizing new and used EV transaction subsidies in a model with inelastic scrappage. Column 4 presents new and used EV transaction subsidies that maximize welfare-weighted total surplus. Column 5 presents total surplus-maximizing new and annual used EV registration subsidies. Column 6 allows the subsidies from column 5 to differ by vehicle class (car, SUV, truck). Column 7 presents the modeled total surplus optimum: vehicle- and age-specific annual taxes that exactly equal the negative externality. Rents include subsidies for eligible consumers. Rent effects are averages across consumers, weighting by baseline choice probabilities. The marginal value of public funds (MVPF) is $(\Delta\text{Consumer surplus} - \Delta\text{Negative externality (excluding gas tax revenue)})/(\text{Subsidy spending} - \Delta\text{Gas tax revenue})$. The "welfare-weighted" total surplus and MVPF weight consumers by 1/income, holding constant the average consumer's weight.

7.2 Non-Stationary Equilibrium

Modeled policies. We now simulate subsidies in non-stationary equilibrium, allowing us to capture time-limited subsidies and a growing EV market. In the model, subsidies are in place for years 1–10 only (as planned under the IRA), and consumers know this with certainty from the beginning of year 1. Our simulations cover 35 years because it takes another 25 years for the effects to work through the resale market. To

match the IRA, the used EV subsidy is available on a vehicle's first transfer *after policy implementation*—for example, a 15-year-old EV that may have been transferred before simulation year 1 is still eligible on its first transfer between years 1 and 10.

Market effects of $4,000 subsidies. Figure 8 presents the effects of universal $4,000 new and used EV subsidies on EV stocks, prices, and scrap rates in non-stationary equilibrium. These plots are analogous to the stationary equilibrium effects plotted in Figure 7, except with simulation year on the x-axis. Each cell's color indicates the effect size, with darker red being more positive, and darker purple being more negative.

The core forces are the same as in stationary equilibrium. New EV subsidies raise new EV sales and thus used EV stocks; the increased used EV supply and reduced used EV demand decrease resale prices and accelerates scrappage. Used EV subsidies increase EV resale prices, increasing new EV sales.

However, there are two key differences from the stationary equilibrium. First, the timing of effects on new EV sales is different between the two subsidies. New EV subsidies have back-loaded effects on new EV sales: the effects grow in years 8–10 as the subsidy end date nears (top middle of Panel (a)). This is because the resale value decreases are weaker after the subsidy ends (year 11 of Panel (c)), since new EVs become less attractive substitutes and eventually there are also fewer substitute young used EVs available (top right of Panel (a)). By contrast, used EV subsidies have front-loaded effects on new EV sales: the effects are strongest in year 1 and turn negative in years 9–10 (top left of Panel (b)). This is because resale values increase most at the beginning, since eventually the additional new EVs work their way into the used market, and the resale value increases end as the subsidy ends (year 11 of Panel (d)).

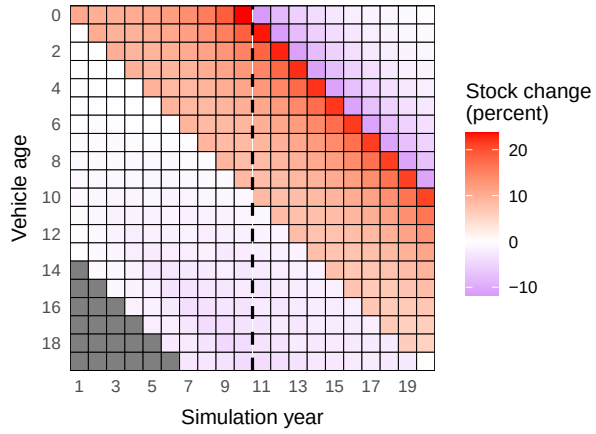
Comparing the top rows of Panels (a) versus (b) shows that ten years of new EV subsidies increase new EV sales for a full ten years, while ten years of used EV subsidies increase new EV sales for only about eight years. This attenuates the modeled environmental benefits from used relative to new EV subsidies. In the model, if used EV subsidies could be credibly pre-announced instead of announced as a surprise in year 1, forward-looking consumers would buy more new EVs in anticipation of higher resale values.

The second substantive difference from the stationary equilibrium is that the used EV subsidy now decreases scrap rates for all used EVs, including older ones (bottom left of Panel (f)). This is because vehicles are eligible for the subsidy on their first transfer *after policy implementation*, so older EVs that may have been transferred before year 1 are still eligible. This restores the corrective benefit from used EV subsidies in reducing scrappage. By contrast, Panel (c) of the earlier Figure 7 showed that in stationary equilibrium, most older EVs are no longer eligible for the subsidy, so their scrap rates increase.

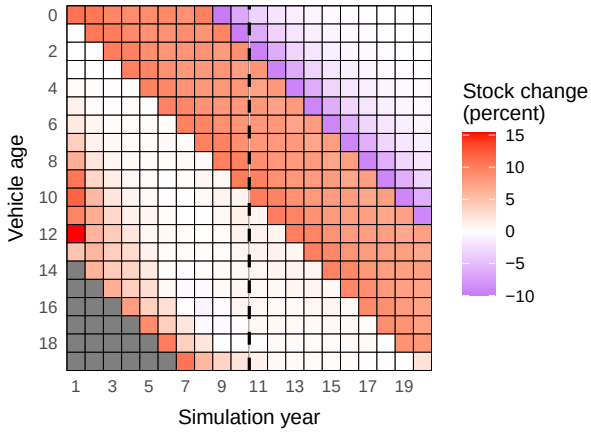
Appendix Figure A16 presents parallel results for GVs. As in the stationary equilibrium, the GV results are generally opposite-signed and smaller.

Figure 8: **Market Effects of EV Subsidies in Non-Stationary Equilibrium**

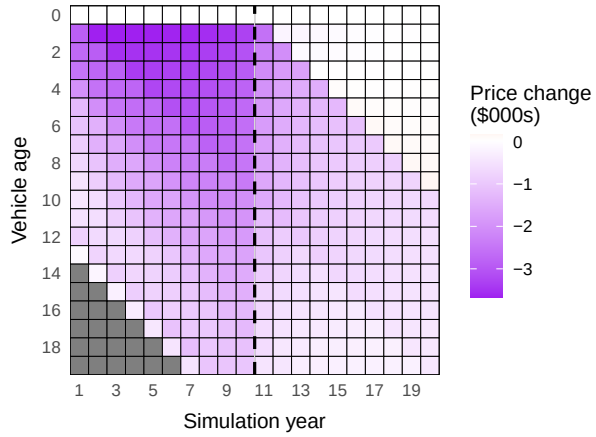
(a) **New Subsidy: Stock Effects**



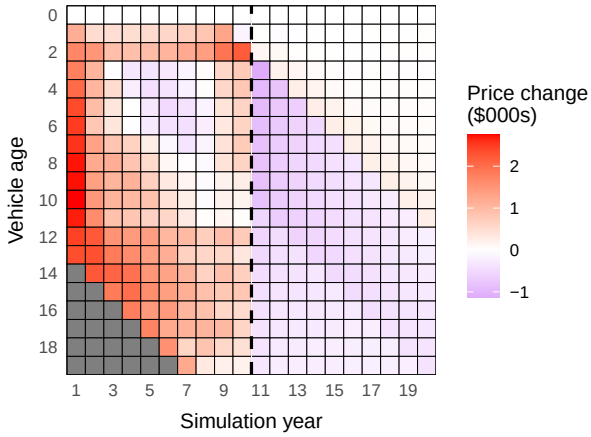
(b) **Used Subsidy: Stock Effects**



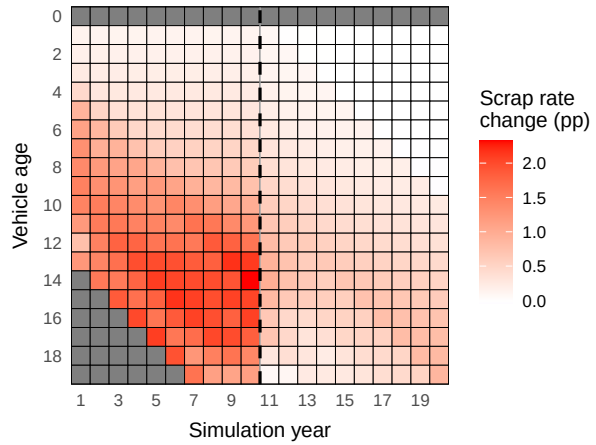
(c) **New Subsidy: Price Effects**



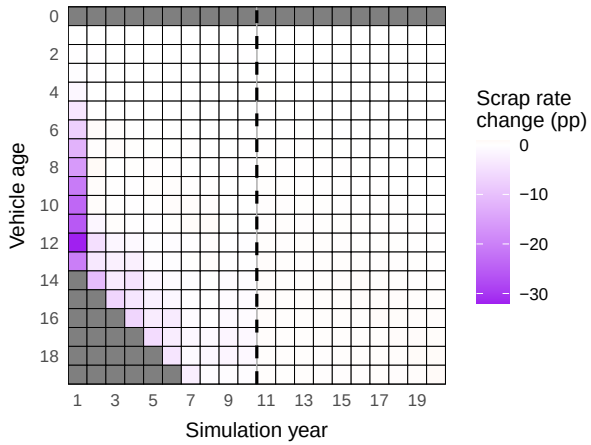
(d) **Used Subsidy: Price Effects**



(e) **New Subsidy: Scrap Rate Effects**



(f) **Used Subsidy: Scrap Rate Effects**



Notes: These figures present the effects of $4,000 new or used EV subsidies on EV stocks, prices, and scrap rates in non-stationary equilibrium by year. At the beginning of simulation year 1, the subsidies are introduced unexpectedly. From that point, consumers know that the subsidies will be available in years 1–10. Price effects are averages across consumers, weighting by baseline choice probabilities. The bottom left of each panel is greyed out because there are no used EVs of those ages in our data.

New and used subsidies and IRA design. Table 8 presents more detailed comparisons of EV subsidies in non-stationary equilibrium. Columns 1 and 2 present universal $4,000 subsidies; these are the same simulations as in Figure 8. Despite the differences brought out by that figure, the two subsidies have broadly similar welfare effects. Both MVPFs are very close to one: 1.02 and 0.99 for new and used EV subsidies, respectively. Both subsidies are regressive, with much larger per-consumer benefits to higher-income people and correspondingly lower welfare-weighted MVPFs.

The table brings out three differences between the two subsidies, the first two of which follow from the discussion of Figure 8. First, the fact that τ_u has front-loaded effects but is not pre-announced eliminates the possible pre-implementation new EV sales increase, reducing externality reduction per dollar of subsidy spending. Second, the fact that τ_u now decreases used EV scrappage (and thus increases EV lifetimes) partially offsets this, increasing externality reduction per dollar of subsidy spending. Third, the back-loaded effects of τ_n combined with our assumption of a growing EV market mean that τ_n has more subsidy spending and proportionally larger consumer surplus and externality reduction than τ_u, even though the MVPF is similar. Put differently, in a growing market, used EV stocks are lower than they will be later, so fewer used EV subsidies are paid out.

Column 3 of Table 8 presents our model's closest approximation to the IRA: $7,500 new EV subsidies with trade restrictions (i.e., limited to car types that satisfy final assembly and battery content requirements), $300,000 buyer income limits, and transaction price limits of $55,000 for cars and $80,000 for SUVs and trucks, plus used EV subsidies of $4,000 or 30 percent of the equilibrium price (whichever is smaller), with $150,000 buyer income limits and $25,000 transaction price limits. Importantly, the effects presented are annual averages over all 35 years of the simulation, of which only the first 10 years have EV subsidies. The effect sizes are thus all smaller than in the stationary equilibrium results tables.

Table 8: **Effects of EV Subsidies in Non-Stationary Equilibrium**

	(1) New subsidy	(2) Used subsidy	(3) IRA
New EV subsidy ($000s)	4	0	Mean ≈ 5.3
Used EV subsidy ($000s)	0	4	Mean ≈ 3.9
Income limit ($000s)	–	–	300/150
Price limit ($000s)	–	–	55-80/25
Panel (a): Market Effects			
ΔAverage EV lifetime (years)	0.03	0.02	0.04
%ΔNew EV sales	0.86	0.36	1.09
%ΔNew + used EV stock	1.17	0.56	1.47
%ΔEV stock / %Δnew EV sales	1.35	1.54	1.34
ΔNew EV average rent ($000s/year)	-0.06	-0.03	-0.05
ΔUsed EV average rent ($000s/year)	-0.04	-0.02	-0.05
Panel (b): Welfare Relative to No Subsidy			
ΔConsumer surplus ($millions/year)	1,884	1,153	2,319
Inc ≥$150k: ΔCS ($/consumer-year)	124	72	137
Inc <$150k: ΔCS ($/consumer-year)	30	16	41
ΔNegative externality ($millions/year)	-170	-103	-259
Subsidy spending ($millions/year)	2,003	1,272	2,732
ΔTotal surplus ($millions/year)	50	-16	-154
ΔWelfare-weighted total surplus ($millions/year)	-513	-323	-622
MVPF	1.02	0.99	0.95
Welfare-weighted MVPF	0.76	0.76	0.79

Notes: This table presents the effects of new and used EV subsidies in non-stationary equilibrium relative to zero EV subsidies. The subsidies are announced at the beginning of year 1 and are known to be in place in years 1–10. We simulate 35 years of non-stationary equilibrium, after which time resale prices take their stationary equilibrium values with no tax credits. All reported results are averages across the 35 simulation years. Columns 1 and 2 present $4,000 new and used EV subsidies with no price or income limits. Column 3 presents our model's closest approximation to the IRA: $7,500 new EV subsidies with trade restrictions, $300,000 buyer income limits, and transaction price limits of $55,000 for cars and $80,000 for SUVs and trucks, plus used EV subsidies of $4,000 or 30 percent of the equilibrium price (whichever is smaller), with $150,000 buyer income limits and $25,000 transaction price limits. Rents include subsidies for eligible consumers. Rent effects are averages across consumers, weighting by baseline choice probabilities. The marginal value of public funds (MVPF) is $(\Delta\text{Consumer surplus} - \Delta\text{Negative externality (excluding gas tax revenue)})/(\text{Subsidy spending} - \Delta\text{Gas tax revenue})$. The "welfare-weighted" total surplus and MVPF weight consumers by 1/income, holding constant the average consumer's weight.

8 Conclusion

This paper's key contribution is to provide a comprehensive evaluation of equity-focused EV subsidy designs, combining clear theoretical insights, a novel bunching estimator, and a detailed structural model of new and used vehicle markets. Our analyses deliver four main policy insights. First, the *delivery* of corrective subsidies matters, not just the *amount*: our bunching estimator shows that the IRA tax credits had much larger effects when delivered immediately at the point of sale instead of as a credit on next year's tax return.

Second, it is important for policymakers to foresee equilibrium responses, not just statutory incidence. As described in the introduction, the motivation for used EV tax credits seems to stem from a "flypaper theory" of incidence, where the benefits stick with lower-income people who buy used cars. Partially consistent with this, our analyses show that new and used EV subsidies are not exactly equivalent, due to flypaper effects from elastic scrappage as well as the front-loaded versus back-loaded effect timing in non-stationary equilibrium. However, because of resale price adjustments, new and used EV subsidies have broadly similar efficiency and distributional effects (as measured by unweighted and welfare-weighted MVPFs).

Third, while earlier analyses modeling only new vehicle sales already suggested that new EV subsidies have MVPFs not far above one (Allcott et al. 2024, Hahn et al. 2026), our results suggest that the MVPF might be even lower than previously believed. Our demand estimates and equilibrium model show that a meaningful minority of diversion to new EVs is from used EVs, not just new GVs, so new EV subsidies accelerate scrappage and increase production externalities, reducing economic efficiency. Fourth, for policymakers who want to balance efficiency and equity considerations, "direct" targeting via new EV subsidies with income limits is more effective than "indirect" targeting via subsidizing used EVs, because used EV subsidies benefit all new EV buyers through higher resale values.

In the time since we first publicly released this paper in 2024, the IRA tax credits we study have been discontinued, U.S. EV demand has dropped (US EIA 2026), Chinese electric vehicles offer an increasing competitive threat (Allcott, Heeney, and Sabal 2026), and the U.S. fiscal situation has worsened. This only increases the value of our insights, as future administrations may revisit EV subsidies for environmental or competitive reasons, with heightened attention to the value of public funds. Moreover, our insights are more broadly relevant for the state and local governments within the U.S. and national governments of other countries that subsidize EVs. Most broadly, our insights have analogies when evaluating subsidies for other clean consumer technologies favored by wealthy consumers, such as solar panels and batteries, and for other goods with resale markets. For example, our theoretical analyses suggest that proposed tax credits for first-time home buyers (Peck 2026) would not just benefit those statutory recipients: by raising house prices, they would also benefit home *sellers*, who are relatively wealthy.

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Online Appendix

Designing Electric Vehicle Subsidies for Equity and Efficiency

Hunt Allcott, Levi Kiefer, Hyuk-soo Kwon, and Tess Snyder

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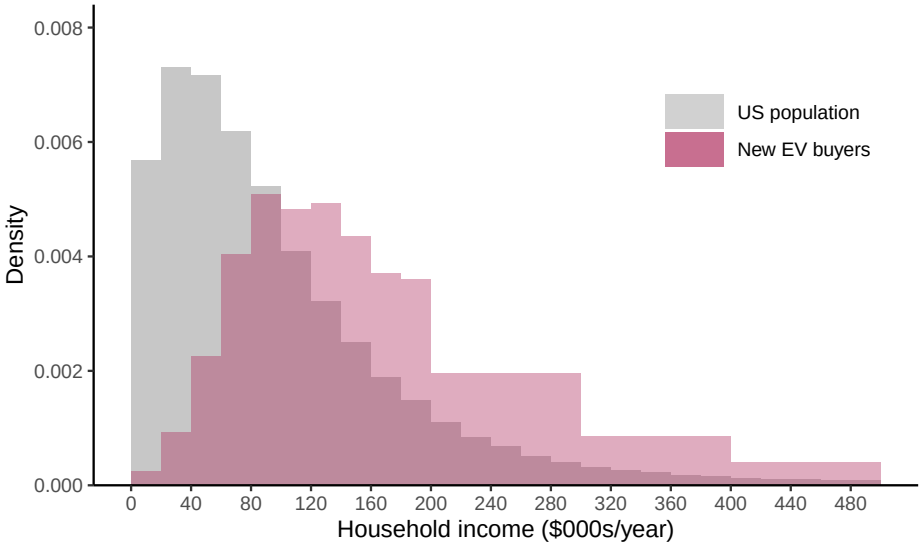
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A Policy Background Appendix

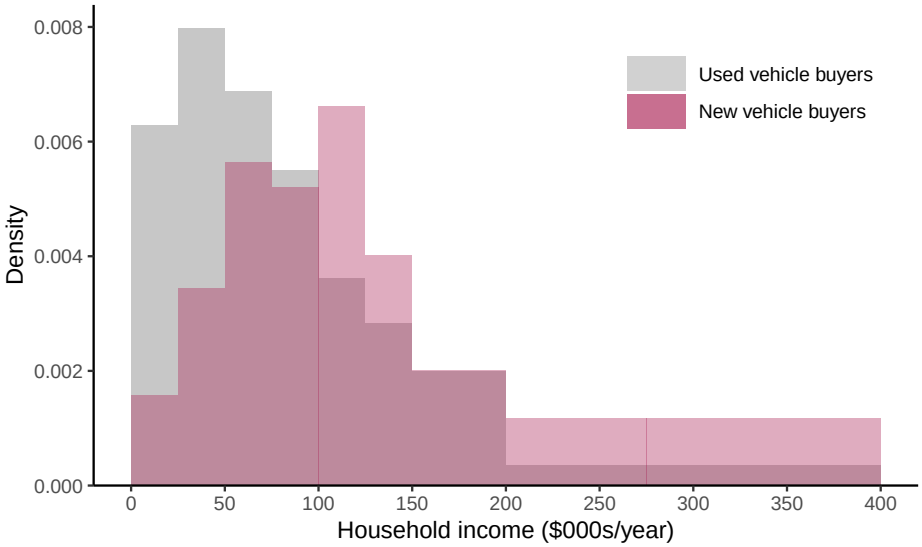
This appendix provides additional context to the summary statistics in Section 2 by presenting full income distributions. Panel (a) of Figure A1 presents the household income distributions for new EV buyers versus the U.S. population, using the 2023 NVES and ACS. This highlights how new EV buyers have substantially higher income than the average American household. Panel (b) of Figure A1 presents the household income distributions for people who bought new versus used cars (including EVs and GVs) in the 12 months before taking the 2022 National Household Travel Survey (NHTS). This demonstrates how used vehicle buyers have lower incomes than new vehicle buyers.

Figure A1: **Household Income Distributions of Vehicle Buyers**

(a) **New Electric Vehicle Buyers versus U.S. Households**



(b) **New versus Used Vehicle Buyers**



Notes: Panel (a) presents the distribution of household income for new electric vehicle buyers in 2023 (from the National Vehicle Experience Survey) and for all U.S. households in 2023 (from the American Community Survey). We truncate the figure at $500,000. Panel (b) presents the distribution of income for people who bought new versus used vehicles in the past 12 months (from the 2022 National Household Travel Survey). In that survey, the top income bin is $200,000 or more; we plot those respondents uniformly between $200,000 and $400,000. All datasets are weighted for national representativeness.

B Theoretical Model Appendix

This appendix presents proofs of all propositions discussed in the body of the paper.

In the body, we assume for expositional simplicity that all new EVs are supplied in perfect competition. In this appendix, we prove the propositions in a more general case with symmetric imperfect competition. We assume that firms produce new EVs at constant marginal cost c and sell them at price p_{nt}. Following Genesove and Mullin (1998) and Weyl and Fabinger (2013), we assume markups are governed by an exogenous "conduct parameter" $\theta := \frac{p_{nt}-c}{p_{nt}}\epsilon_D$, where $\epsilon_D > 0$ is the new vehicle market demand elasticity.

Propositions 1 and 5 are unchanged. Propositions 2–4 are as reported in the body after setting $\theta = 0$, or after redefining ϕ_n as the original negative production externality net of the markup.

B.1 Price and Quantity Effects in Stationary Equilibrium

This appendix presents equilibrium price and quantity effects of marginal subsidy changes in stationary equilibrium. We use these results throughout the proofs in the subsequent appendices.

The stationary equilibrium price effects are

$$\begin{aligned} \frac{dp_n}{d\tau_n} &\geq 0, \quad \frac{dp_n}{d\tau_u} \lesseqgtr 0 \\ \frac{dp_u}{d\tau_n} &\leq 0, \quad \frac{dp_u}{d\tau_u} \geq 0. \end{aligned} \tag{5}$$

The quantity effects are

$$\begin{aligned} \frac{dD_n}{d\tau_n} &\geq 0, \quad \frac{dD_n}{d\tau_u} \lesseqgtr 0 \\ \frac{dD_u}{d\tau_n} &\lesseqgtr 0, \quad \frac{dD_u}{d\tau_u} \geq 0. \end{aligned} \tag{6}$$

These comparative statics have three implications. First, both new and used EV subsidies increase prices and quantities of the corresponding age vehicles. Second, new EV subsidies decrease used EV prices, both by reducing used EV demand and by increasing used EV supply. These two channels generate an ambiguous effect on used EV quantities. If new-used substitution D_c' is small, then the supply increase dominates, increasing quantities. But if D_c' is large, then the demand decrease dominates, decreasing quantities. In our empirical estimates, new-used substitution is limited, so we can expect the supply increase to dominate.

Third, used EV subsidies have similarly ambiguous effects on new EV prices and quantities. The resale price increase shifts new EV demand outward, but the used vehicle rent decrease shifts new EV demand inward. If D_c' is small, then the outward shift dominates, increasing prices and quantities. But if D_c' is large, then the inward shift dominates, decreasing prices and quantities.

The rest of this appendix subsection derives these comparative statics. The derivations employ two market clearing conditions:

$$D_u(p_n - \mu\tau_n - v(p_u), p_u - \mu\tau_u - v^s) = (1-g)D_n(p_n - \mu\tau_n - v(p_u), p_u - \mu\tau_u - v^s) \tag{7}$$

$$p_n - c = \frac{-\theta}{D'_n} D_n, \tag{8}$$

where the first is market clearing condition and the second is the firm FOC.

Define $\chi = [2(1-g)D'_c + \theta D'^2_c/D'_n] - (1-g)^2 D'_n - (1+\theta)g' D_n - (1+\theta)D'_u$. This will also be used below. Note that our regularity condition that $(1-g)\cdot|D'_a| > D'_c$ given in the body is sufficient to guarantee this is positive.

B.1.1 Price Effects of New EV Subsidies

For the effects of new vehicle subsidies, we totally differentiate our two equilibrium conditions with respect to τ_n, yielding

$$\frac{dp_n}{d\tau_n} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right] + D'_c\frac{dp_u}{d\tau_n}\right) \tag{9}$$

$$D'_c\left(\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right) + D'_u\frac{dp_u}{d\tau_n} = (1-g)\left(D'_n\left[\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right] + D'_c\frac{dp_u}{d\tau_n}\right) - g' D_n\frac{dp_u}{d\tau_n}. \tag{10}$$

Rearranging gives

$$\frac{dp_n}{d\tau_n} = \frac{\mu\theta + \theta(1-g)\frac{dp_u}{d\tau_n} - \theta\frac{dp_u}{d\tau_n}\frac{D'_c}{D'_n}}{1+\theta} \tag{11}$$

$$\frac{dp_n}{d\tau_n} = \frac{\mu(1-g)D'_n - \mu D'_c + \frac{dp_u}{d\tau_n}\left(g' D_n + D'_u - 2(1-g)D'_c + (1-g)^2 D'_n\right)}{(1-g)D'_n - D'_c}. \tag{12}$$

The final incidence values are then

$$\frac{dp_n}{d\tau_n} = \mu\frac{\theta\left(\frac{D'_c D'_c}{D'_n} - D'_u - g' D_n\right)}{\chi} \geq 0 \tag{13}$$

$$\frac{dp_u}{d\tau_n} = \mu\frac{(1-g)D'_n - D'_c}{\chi} \leq 0. \tag{14}$$

B.1.2 Price Effects of Used EV Subsidies

For the effects of used vehicle subsidies, we totally differentiate our two equilibrium conditions with respect to τ_u, yielding

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D'_c\left[\frac{dp_u}{d\tau_u} - \mu\right]\right) \tag{15}$$

$$D'_c\left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) + D'_u\left(\frac{dp_u}{d\tau_u} - \mu\right) = (1-g)\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D'_c\left[\frac{dp_u}{d\tau_u} - \mu\right]\right) - g'D_n\frac{dp_u}{d\tau_u}. \tag{16}$$

Rearranging gives

$$\frac{dp_n}{d\tau_u} = \frac{\theta(1-g)\frac{dp_u}{d\tau_u} - \theta\frac{D'_c}{D'_n}\frac{dp_u}{d\tau_u} + \mu\theta\frac{D'_c}{D'_n}}{1+\theta} \tag{17}$$

$$\frac{dp_n}{d\tau_u} = \frac{\mu(1-g)D'_c - \mu D'_u + \frac{dp_u}{d\tau_u}\left[(1-g)^2D'_n - 2(1-g)D'_c + g'D_n + D'_u\right]}{(1-g)D'_n - D'_c}. \tag{18}$$

Solving this system gives

$$\frac{dp_n}{d\tau_u} = \mu\frac{\theta(1-g)\left[\frac{D'_cD'_c}{D'_n} - D'_u\right] - \theta g'D_n\frac{D'_c}{D'_n}}{\chi} \lesseqgtr 0 \tag{19}$$

$$\frac{dp_u}{d\tau_u} = \mu\frac{(1-g)D'_c - (1+\theta)D'_u + \theta\frac{D'_cD'_c}{D'_n}}{\chi} \geq 0. \tag{20}$$

B.1.3 Quantity Effects

We start with the new demand derivatives using the firm FOC.

$$\frac{dp_n}{d\tau_n} = \frac{-\theta}{D'_n}\frac{dD_n}{d\tau_n} \implies \frac{dD_n}{d\tau_n} = \frac{-D'_n}{\theta}\frac{dp_n}{d\tau_n} \geq 0 \tag{21}$$

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\frac{dD_n}{d\tau_u} \implies \frac{dD_n}{d\tau_u} = \frac{-D'_n}{\theta}\frac{dp_n}{d\tau_u} \lesseqgtr 0. \tag{22}$$

For the used demand derivatives, we use the market clearing condition $(1-g)D_n = D_u$.

$$\begin{aligned}
\frac{dD_u}{d\tau_n} &= (1-g)\frac{dD_n}{d\tau_n} - g'\frac{dp_u}{d\tau_n}D_n \\
&= -(1-g)\frac{dp_n}{d\tau_n}\frac{D'_n}{\theta} - g'D_n\frac{dp_u}{d\tau_n} \\
&= \frac{\frac{-D'_n}{\theta}(1-g)\mu\theta\left(\frac{D'_cD'_c}{D'_n} - D'_u - g'D_n\right) - \mu g'D_n\left((1-g)D'_n - D'_c\right)}{\chi} \\
&= \mu\frac{(1-g)\left[D'_uD'_n - D'_cD'_c\right] + g'D_nD'_c}{\chi} \lesseqgtr 0
\end{aligned} \tag{23}$$

and

$$\begin{aligned}\frac{dD_u}{d\tau_u} &= (1-g)\frac{dD_n}{d\tau_u} - g'\frac{dp_u}{d\tau_u}D_n \\ &= -(1-g)\frac{dp_n}{d\tau_u}\frac{D'_n}{\theta} - g'\frac{dp_u}{d\tau_u}D_n \\ &= \frac{\frac{-D'_n}{\theta}(1-g)\mu\theta\left[(1-g)\cdot\left(\frac{D'_cD'_c}{D'_n} - D'_u\right) - g'D_n\frac{D'_c}{D'_n}\right] - \mu g'D_n\left[(1-g)D'_c - (1+\theta)D'_u + \theta\frac{D'_cD'_c}{D'_n}\right]}{\chi} \\ &= \mu\frac{(1-g)^2\cdot(D'_nD'_u - D'_cD'_c) + g'D_n\left[(1+\theta)D'_u - \theta\frac{D'_cD'_c}{D'_n}\right]}{\chi} \geq 0. \end{aligned} \tag{24}$$

B.2 Proof of Proposition 1

We use the stationary equilibrium price derivatives given in Appendix B.1 to compute the rent derivatives below. We assume $\mu = 1$, but the results hold for $\mu < 1$.

B.2.1 New EV Rent

We first differentiate the rents individually

$$(1-g)\frac{dr_n}{d\tau_n} = (1-g)\left[\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}\right] = (1-g)\frac{-(1-g)D'_c + g'D_n + D'_u}{\chi} < 0 \tag{25}$$

$$\frac{dr_n}{d\tau_u} = \frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u} = \frac{(1-g)D'_u - (1-g)^2D'_c - \frac{\theta g'D_nD'_c}{D'_n}}{\chi} < 0. \tag{26}$$

Subtracting the two we get

$$(1-g)\frac{dr_n}{d\tau_n} - \frac{dr_n}{d\tau_u} = \frac{(1-g)g'D_n + \theta g'D_n\frac{D'_c}{D'_n}}{\chi} = \frac{g'D_n\left[(1-g) + \frac{\theta D'_c}{D'_n}\right]}{\chi} \tag{27}$$

We want to show that equation (27) is less than or equal to 0. For this to be true, $D'_c \leq -(1-g)D'_n/\theta$, which is implied by our regularity condition, since $0 < \theta \leq 1$. When $g' = 0$, equation (27) is 0, implying equal (scaled) rent effects.

B.2.2 Used EV Rent

We first differentiate the rents individually

$$(1-g)\frac{dr_u}{d\tau_n} = (1-g)\frac{dp_u}{d\tau_n} = \frac{(1-g)^2 D_n' - (1-g)D_c'}{\chi} < 0 \tag{28}$$

$$\frac{dr_u}{d\tau_u} = \frac{dp_u}{d\tau_u} - 1 = \frac{(1-g)^2 D_n' + (1+\theta)g' D_n - (1-g)D_c'}{\chi} < 0. \tag{29}$$

Combining we get

$$(1-g)\frac{dr_u}{d\tau_n} - \frac{dr_u}{d\tau_u} = \frac{-(1+\theta)g' D_n}{\chi} \geq 0, \tag{30}$$

which shows $\frac{dr_u}{d\tau_u} \leq (1-g)\frac{dr_u}{d\tau_n}$. When $g' = 0$, the (scaled) rent effects are equal.

B.2.3 Policy Injectivity

Assume full eligibility ($\mu = 1$), then we want to prove that the mapping f of policies to equilibrium quantities $(\tau_n, \tau_u) \to (D_n, D_u)$ is injective if and only if $g' < 0$. We wrote an implication of this statement in the exposition of Proposition 1: if $g' = 0$, linear combinations of subsidies can produce the same market outcomes.

For the forward direction, we prove the contrapositive: if $g' = 0$, then the policy map is not injective. It is sufficient to consider a general policy (τ_n, τ_u) and construct a nonequivalent policy $(\tilde{\tau}_n, \tilde{\tau}_u)$ that generates the same outcomes. Since $g' = 0$, scrappage will be constant, so these policies will generate the same equilibrium outcomes if the rental prices r_n and r_u are unchanged. Let $\Delta \neq 0$. Suppose $\tilde{\tau}_n = \tau_n + (1-g)\Delta$ and $\tilde{\tau}_u = \tau_u - \Delta$. Let r_n and r_u be the rental prices under (τ_n, τ_u). The rental derivatives are independent of τ so

$$\tilde{r}_n = r_n + \frac{dr_n}{d\tau_n}(1-g)\Delta - \frac{dr_n}{d\tau_u}\Delta = r_n + \Delta\left[(1-g)\frac{dr_n}{d\tau_n} - \frac{dr_n}{d\tau_u}\right] = r_n \tag{31}$$

$$\tilde{r}_u = r_u + \frac{dr_u}{d\tau_n}(1-g)\Delta - \frac{dr_u}{d\tau_u}\Delta = r_u + \Delta\left[(1-g)\frac{dr_u}{d\tau_n} - \frac{dr_u}{d\tau_u}\right] = r_u. \tag{32}$$

For the reverse direction, we want to show that if $g' < 0$, the policy mapping is injective. To show this, suppose there are two policies (τ_n, τ_u) and $(\tilde{\tau}_n, \tilde{\tau}_u)$ that generate the same market outcomes. By market clearing $(1 - g(p_u)) = D_u/D_n$. If $g' < 0$ on the relevant domain, then equal quantities implies that $p_u = \tilde{p}_u$.

Next, the firm optimality condition says $p_n - c = -\theta D_n / D_n'$. Since D_n is equivalent under both policies and D_n' is constant, $p_n = \tilde{p}_n$. Differencing the demand equations and using linearity of demand gives us

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} D_n' & D_c' \\ D_c' & D_u' \end{bmatrix} \begin{bmatrix} r_n - \tilde{r}_n \\ r_u - \tilde{r}_u \end{bmatrix}. \tag{33}$$

By assumption $D'_n D'_u - {D'_c}^2 > 0$ so the matrix of demand derivatives is invertible and thus $r_n = \tilde{r}_n$ and $r_u = \tilde{r}_u$. By definition of r_n and r_u plus the above price equalities, $r_n - \tilde{r}_n = -\tau_n + \tilde{\tau}_n = 0$ and $r_u - \tilde{r}_u = -\tau_u + \tilde{\tau}_u = 0$. Thus the two policies are identical $(\tau_n, \tau_u) = (\tilde{\tau}_n, \tilde{\tau}_u)$ and the mapping is injective.

B.3 Proof of Proposition 2

For this proof we assume finite types ($|I| < \infty$), but the results hold in full generality. Suppose for now $g' < 0$, we show equivalence when $g' = 0$ in the next subsection. Define $D_a := \frac{\sum_i D_{ia}}{|I|}$. One period of welfare W can be expressed as

$$W = \sum_i \frac{w_i CS_i}{|I|} + D_n \cdot (p_n - c + \phi - \phi_n - \tau_n) + D_u \cdot (\phi - \tau_u), \tag{34}$$

where CS_i represents consumer surplus for consumer i with welfare weight w_i. Before taking first-order conditions, we consider the derivative of consumer surplus for consumer i under our two-good setup. The consumer faces a constrained optimization problem to choose $D_n(\cdot), D_u(\cdot)$ to maximize consumer surplus subject to budget constraint B. Denote effective prices $(\bar{p}_n, \bar{p}_u) = (p_n - \tau_n - v, p_u - \tau_u - v^s)$, which only enter the value function indirectly. Therefore, it is a standard application of the envelope theorem that

$$\frac{dCS}{d\bar{p}_x} = \lambda(\bar{p}_n, \bar{p}_u)\frac{\partial B}{\partial \bar{p}_x} = -\lambda \cdot D_x, \tag{35}$$

where λ is the Lagrange multiplier on the budget constraint and is therefore one by quasilinearity. We thus have

$$\frac{dCS(\bar{p_n}, \bar{p_u})}{d\tau_x} = \frac{dCS}{d\bar{p_n}}\frac{d\bar{p_n}}{d\tau_x} + \frac{dCS}{d\bar{p_u}}\frac{d\bar{p_u}}{d\tau_x} = -D_n \cdot \frac{d(p_n - \tau_n - v)}{d\tau_x} - D_u \cdot \frac{d(p_u - \tau_u - v^s)}{d\tau_x}, \tag{36}$$

for both τ_n and τ_u.

We now differentiate with respect to τ_n and τ_u,

$$\begin{aligned}\frac{dW}{d\tau_n} = &-\sum_i \frac{w_i}{|I|}\left[D_{in} \cdot \left(\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}\right) + D_{iu} \cdot \frac{dp_u}{d\tau_n}\right] + D_n \cdot \left(\frac{dp_n}{d\tau_n} - 1\right) \\ &+ \frac{dD_n}{d\tau_n} \cdot (p_n - c + \phi - \phi_n - \tau_n) + \frac{dD_u}{d\tau_n}(\phi - \tau_u) \qquad (37) \\ \frac{dW}{d\tau_u} = &-\sum_i \frac{w_i}{|I|}\left[D_{in} \cdot \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) + D_{iu} \cdot \left(\frac{dp_u}{d\tau_u} - 1\right)\right] + D_n \cdot \frac{dp_n}{d\tau_u} \\ &+ \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \phi_n - \tau_n) - D_u + \frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u). \qquad (38)\end{aligned}$$

Rearranging and simplifying gives

$$\begin{aligned}\frac{dD_n}{d\tau_n}(p_n - c + \phi - \phi_n - \tau_n) + \frac{dD_u}{d\tau_n}\cdot(\phi - \tau_u) &= \left(D_n - \frac{\sum_i w_i D_{in}}{|I|}\right) + \frac{dp_n}{d\tau_n}\left(\frac{\sum_i w_i D_{in}}{|I|} - D_n\right) \\ &\quad + \frac{dp_u}{d\tau_n}\frac{\sum_i (w_i D_{iu} - (1-g) w_i D_{in})}{|I|} \\ &= \frac{dr_n}{d\tau_n}\cdot\left(\frac{\sum_i w_i D_{in}}{|I|} - D_n\right) + \frac{dr_u}{d\tau_n}\cdot\left(\frac{\sum_i w_i D_{iu}}{|I|} - D_u\right)\end{aligned} \tag{39}$$

$$\begin{aligned}\frac{dD_n}{d\tau_u}(p_n - c + \phi - \phi_n - \tau_n) + \frac{dD_u}{d\tau_u}(\phi - \tau_u) &= \left(D_u - \frac{\sum_i w_i D_{iu}}{|I|}\right) + \frac{dp_n}{d\tau_u}\left(\frac{\sum_i w_i D_{in}}{|I|} - D_n\right) \\ &\quad + \frac{dp_u}{d\tau_u}\frac{\sum_i (w_i D_{iu} - (1-g) w_i D_{in})}{|I|} \\ &= \frac{dr_n}{d\tau_u}\cdot\left(\frac{\sum_i w_i D_{in}}{|I|} - D_n\right) + \frac{dr_u}{d\tau_u}\cdot\left(\frac{\sum_i w_i D_{iu}}{|I|} - D_u\right).\end{aligned} \tag{40}$$

Note that provided $\bar{w} = 1$,

$$Cov(w_i, D_{ia}) = \frac{\sum_i (w_i - \bar{w_i})(D_{ia} - \bar{D}_{ia})}{|I|} = \frac{\sum_i w_i D_{ia}}{|I|} - \frac{\sum_i D_{ia}}{|I|} = \frac{\sum_i w_i D_{ia}}{|I|} - D_a, \tag{41}$$

and let $b_a \coloneqq Cov(w_i, D_{ia})$.

We can then simplify the two FOCs further:

$$\frac{dD_n}{d\tau_n}\cdot(p_n - c + \phi - \phi_n - \tau_n) + \frac{dD_u}{d\tau_n}\cdot(\phi - \tau_u) = b_n\cdot\frac{dr_n}{d\tau_n} + b_u\frac{dr_u}{d\tau_n} \tag{42}$$

$$\frac{dD_n}{d\tau_u}\cdot(p_n - c + \phi - \phi_n - \tau_n) + \frac{dD_u}{d\tau_u}\cdot(\phi - \tau_u) = b_n\cdot\frac{dr_n}{d\tau_u} + b_u\frac{dr_u}{d\tau_u}. \tag{43}$$

Express this in matrix form as

$$\begin{bmatrix}\frac{dD_n}{d\tau_n} & \frac{dD_u}{d\tau_n} \\ \frac{dD_n}{d\tau_u} & \frac{dD_u}{d\tau_u}\end{bmatrix}\begin{bmatrix}p_n - c + \phi - \phi_n - \tau_n \\ \phi - \tau_u\end{bmatrix} = \begin{bmatrix}\frac{dr_n}{d\tau_n} & \frac{dr_u}{d\tau_n} \\ \frac{dr_n}{d\tau_u} & \frac{dr_u}{d\tau_u}\end{bmatrix}\begin{bmatrix}b_n \\ b_u\end{bmatrix}. \tag{44}$$

Let R be the Jacobian of $\boldsymbol{r} = [r_n, r_u]$ with respect to $\boldsymbol{\tau} = [\tau_n, \tau_u]$, D be the Jacobian of $[D_n, D_u]$ with respect to $\boldsymbol{r}$, and J be the matrix of total derivatives of $[D_n, D_u]$ with respect to $\boldsymbol{\tau}$. Then equation (44) is equivalent to

$$J^T\begin{bmatrix}p_n - c + \phi - \phi_n - \tau_n \\ \phi - \tau_u\end{bmatrix} = R^T\begin{bmatrix}b_n \\ b_u\end{bmatrix}. \tag{45}$$

The chain rule can be expressed as $J = DR$, thus

$$R^T D^T \begin{bmatrix} p_n - c + \phi - \phi_n - \tau_n \\ \phi - \tau_u \end{bmatrix} = R^T \begin{bmatrix} b_n \\ b_u \end{bmatrix}. \tag{46}$$

By Proposition 1, denote $c_1 = (1-g)\frac{dr_n}{d\tau_n} - \frac{dr_n}{d\tau_u} < 0$ and $c_2 = (1-g)\frac{dr_u}{d\tau_n} - \frac{dr_u}{d\tau_u} > 0$ (where the strict inequalities follow from $g' < 0$),

$$\begin{aligned} \frac{dr_n}{d\tau_n} \cdot \frac{dr_u}{d\tau_u} - \frac{dr_n}{d\tau_u} \cdot \frac{dr_u}{d\tau_n} &= \frac{dr_n}{d\tau_n}\left[(1-g)\frac{dr_u}{d\tau_n} - c_2\right] - \frac{dr_u}{d\tau_n}\left[(1-g)\frac{dr_n}{d\tau_n} - c_1\right] \\ &= -c_2\frac{dr_n}{d\tau_n} + c_1\frac{dr_u}{d\tau_n} > 0, \end{aligned} \tag{47}$$

thus R is invertible and R^{-1} exists. Furthermore, $D^{T^{-1}} = \frac{1}{D'_n D'_u - {D'_c}^2}\begin{bmatrix} D'_u & -D'_c \\ -D'_c & D'_n \end{bmatrix}$, and thus

$$\tau_n^* = p_n - c + \phi - \phi_n - \frac{b_n D'_u - b_u D'_c}{D'_n D'_u - {D'_c}^2} \tag{48}$$

$$\tau_u^* = \phi + \frac{b_n D'_c - b_u D'_n}{D'_n D'_u - {D'_c}^2}. \tag{49}$$

To address the text following the proposition, consider the sum of the numerators in the redistributive terms

$$[b_n D'_u - b_u D'_c] + [b_n D'_c - b_u D'_n] = b_n\left(D'_u + D'_c\right) - b_u(D'_c + D'_n). \tag{50}$$

The redistributive term is more negative for τ_n^* if equation (50) is positive meaning $\frac{b_n}{D'_n + D'_c} > \frac{b_u}{D'_u + D'_c}$. In the body we reference high-income buyers more strongly preferring new EVs after normalizing by net demand slopes, which is exactly this condition (i.e., $b_n < b_u$ post-normalization).

We can also explore the conditions under which welfare weights imply a positive redistributive term for τ_u^* and negative for τ_n^*. For this to be true and $b_u > 0$, we must have

$$b_n D'_u - b_u D'_c \geq 0 \iff \frac{-b_n}{b_u} \geq \frac{D'_c}{|D'_u|}, \quad \text{and} \tag{51}$$

$$b_n D'_c - b_u D'_n \geq 0 \iff \frac{-b_n}{b_u} \leq \frac{|D'_n|}{D'_c}, \tag{52}$$

which is equivalent to saying that

$$\frac{D'_c}{|D'_u|} \leq \frac{-b_n}{b_u} \leq \frac{|D'_n|}{D'_c}. \tag{53}$$

Equation (53) is a general restriction and since the LHS is bounded above by 1 and the RHS is bounded below by 1, it shows that there exists an interval of possible b_n and b_u values where welfare weights increase τ_u^* and decrease τ_n^*. This interval widens as D_c' decreases. One sufficient assumption is that $\forall i, D_{in} + D_{iu} = D$, which implies

$$b_u = \text{Cov}\left(w_i, D_{iu}\right) = \text{Cov}\left(w_i, D - D_{in}\right) = \text{Cov}\left(w_i, -D_{in}\right) = -b_n, \tag{54}$$

and is contained in the interval.

The weaker version where all consumers buy D vehicles across both EV and GV markets, as opposed to the condition $D_{in} + D_{iu} = D, \forall i$, is insufficient to sign the effects of welfare weights in full generality. This is because we only explicitly model the EV market. For example, consider a model of two groups with equal used EV demand but higher new EV demand in the higher-income group. This implies that $b_u = 0$ and $b_n < 0$, which would lower both τ_n^* and τ_u^* relative to uniform welfare weights. This example also shows why having D_{in}/D_{iu} increase with income is insufficient to bound the effects of welfare weights. In essence, we need sufficient used EV demand from lower income individuals to generate a positive redistributive term for τ_u^* and negative for τ_n^*.

B.3.1 Perfectly Inelastic Scrappage

Now suppose that $g' = 0$. In the proof of policy injectivity in Appendix B.2.3 we established that for $\forall \Delta \in \mathbb{R}$ and $\tilde{\tau}_n = \tau_n + (1-g)\Delta$ and $\tilde{\tau}_u = \tau_u - \Delta$, then the policies (τ_n, τ_u) and $(\tilde{\tau}_n, \tilde{\tau}_u)$ have the same outcomes when $g' = 0$.

Now consider any two policies where $\tilde{\tau}_n + (1-g)\tilde{\tau}_u = \tau_n^* + (1-g)\tau_u^*$, then this is equivalent to for any fixed Δ that

$$\tilde{\tau}_n = \tau_n^* + (1-g)\Delta \quad \text{and} \quad \left[(1-g)\tilde{\tau}_u = (1-g)\tau_u^* - (1-g)\Delta \iff \tilde{\tau}_u = \tau_u^* - \Delta\right]. \tag{55}$$

Therefore, $(\tilde{\tau}_n, \tilde{\tau}_u)$ and (τ_n^*, τ_u^*) are equivalent policies.

B.4 Connection to the Many-Person Ramsey Rule

The redistributive terms in Proposition 2 are a two-good version of the many-person Ramsey rule in Diamond (1975). Diamond considers consumers indexed by h, where x_k^h is consumer h's demand for commodity k, γ^h is her social marginal utility of income, λ is the multiplier on the government budget constraint, t_i is the excise tax on commodity i, and s_{ik}^h is a compensated Slutsky derivative. Diamond's first-order condition can be written as

$$\sum_h \left(\gamma^h - \lambda\right) x_k^h = \lambda \sum_i t_i \sum_h s_{ik}^h. \tag{56}$$

With an optimal poll tax, λ equals the average social marginal utility of income. Thus, the left-hand side of equation (56) is proportional to the covariance between individual demand for good k and the social marginal utility of income. The rule balances this redistributive benefit against the compensated demand distortions generated by commodity taxation.

To connect this result to our setting, consider the full-eligibility case and normalize welfare weights to have average one: $w_i = \gamma^i/\lambda$. Because Diamond writes taxes while we write subsidies, let $t_a = -\tau_a$. Equation (56) then implies

$$\begin{pmatrix} D'_n & D'_c \\ D'_c & D'_u \end{pmatrix} \begin{pmatrix} t_n \\ t_u \end{pmatrix} = \begin{pmatrix} \text{Cov}(w_i, D_{in}) \\ \text{Cov}(w_i, D_{iu}) \end{pmatrix}. \tag{57}$$

Equivalently, the redistributive component of the optimal subsidy vector is

$$\begin{pmatrix} \tau_n^{\text{redist}} \\ \tau_u^{\text{redist}} \end{pmatrix} = -\begin{pmatrix} D'_n & D'_c \\ D'_c & D'_u \end{pmatrix}^{-1} \begin{pmatrix} \text{Cov}(w_i, D_{in}) \\ \text{Cov}(w_i, D_{iu}) \end{pmatrix}. \tag{58}$$

Our model differs from Diamond's setting in two respects. First, Proposition 2 captures environmental externalities from EV production and use, which are absent from Diamond's commodity-tax problem. Second, the relevant prices in our model are equilibrium rental prices, which incorporate resale-market and scrappage responses. Nevertheless, conditional on these equilibrium rental prices, the redistributive component is exactly the many-person Ramsey logic applied to new and used EVs.

B.5 Optimal New EV Subsidy with Zero Used EV Subsidy

This appendix section provides a proof of Proposition 3.

With welfare weights uniformly one and assuming $\tau_u = 0$, we can write welfare as

$$W = CS + D_n \cdot (p_n - c - \phi_n + (2-g)\phi - \tau_n). \tag{59}$$

Differentiating, we then get

$$\begin{aligned} \left.\frac{dW}{d\tau_n}\right|_{\tau_u=0} = 0 = &-D_n \cdot \left(\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}\right) - D_u \frac{dp_u}{d\tau_n} + \frac{dD_n}{d\tau_n}(p_n - c - \phi_n + (2-g)\phi - \tau_n) \\ &+ D_n \left(\frac{dp_n}{d\tau_n} - \frac{dg}{d\tau_n}\phi - 1\right) \\ \tau_n^{**} = &\, p_n - c - \phi_n + \phi\left[2 - g - \frac{D_n \cdot dg/d\tau_n}{dD_n/d\tau_n}\right]. \end{aligned} \tag{60}$$

B.6 Type-Specific Optimal Policy Derivation

In this appendix section, we consider a setting with $|I| < \infty$ different consumer types, each with welfare weight w_i. We adopt the same assumption as Appendix B.3 that $D_a = \frac{\sum_i D_{ia}}{|I|}$. We allow type-specific subsidy levels τ_{in} and τ_{iu}. Consequently, our welfare equation will be

$$W = \sum_i \frac{w_i CS_i}{|I|} + D_n \cdot (p_n - c + \phi - \phi_n) + \phi D_u - \frac{\sum_i (D_{in}\tau_{in} + D_{iu}\tau_{iu})}{|I|}. \tag{61}$$

We now derive the optimal subsidy for a fixed consumer-type j. Differentiating our welfare function with respect to τ_{jn} yields

$$\frac{dW}{d\tau_{jn}} = 0 = -\sum_i \frac{w_i}{|I|}\left[D_{in}\cdot\left(\frac{dp_n}{d\tau_{jn}} - (1-g)\frac{dp_u}{d\tau_{jn}}\right) + D_{iu}\cdot\frac{dp_u}{d\tau_{jn}}\right] + \frac{w_j D_{jn}}{|I|} + D_n\frac{dp_n}{d\tau_{jn}} + \frac{dD_n}{d\tau_{jn}}\cdot(p_n - c + \phi - \phi_n) + \phi\frac{dD_u}{d\tau_{jn}} - \frac{D_{jn}}{|I|} - \frac{1}{|I|}\sum_i\left[\frac{dD_{in}}{d\tau_{jn}}\tau_{in} + \frac{dD_{iu}}{d\tau_{jn}}\tau_{iu}\right]. \tag{62}$$

Note that $\forall i \neq j$ $\frac{dD_{ia}}{d\tau_{jn}}$ are equivalent for $a \in \{n, u\}$. For $i = j$, $\frac{dD_{jn}}{d\tau_{jn}} = \frac{dD_{j'n}}{d\tau_{jn}} - D'_n$ where $j' \neq j$ and $\frac{dD_{ju}}{d\tau_{jn}} = \frac{dD_{j'u}}{d\tau_{jn}} - D'_c$. We can then write

$$\begin{aligned}\sum_i \frac{dD_{in}}{d\tau_{jn}}\tau_{in} &= \sum_{i\neq j}\frac{dD_{in}}{d\tau_{jn}}\tau_{in} + \left(\frac{dD_{nj'}}{d\tau_{jn}} - D'_n\right)\tau_{jn} \\ &= |I|\frac{dD_n}{d\tau_{jn}}\bar{\tau}_n - D'_n(\tau_{jn} - \bar{\tau}_n).\end{aligned} \tag{63}$$

An equivalent argument gives $\sum_i \frac{dD_{iu}}{d\tau_{jn}}\tau_{iu} = |I|\frac{dD_u}{d\tau_{jn}}\bar{\tau}_u - D'_c(\tau_{ju} - \bar{\tau_u})$. Simplifying the FOC and using the covariance formulas as in Proposition 2 gives

$$\begin{aligned}\frac{dD_n}{d\tau_{jn}}(p_n - c + \phi - \phi_n - \bar{\tau}_n) + \frac{dD_u}{d\tau_{jn}}(\phi - \bar{\tau}_u) + \frac{D'_n}{|I|}(\tau_{jn} - \bar{\tau}_n) + \frac{D'_c}{|I|}(\tau_{ju} - \bar{\tau}_u) = \\ (1 - w_j)\frac{D_{jn}}{|I|} + b_n\frac{dp_n}{d\tau_{jn}} + \frac{dp_u}{d\tau_{jn}}(b_u - (1-g)b_n).\end{aligned} \tag{64}$$

The FOC for the corresponding used subsidy τ_{uj} gives

$$\frac{dW}{d\tau_{ju}} = 0 = -\sum_i \frac{w_i}{|I|}\left[D_{in}\cdot\left(\frac{dp_n}{d\tau_{ju}} - (1-g)\frac{dp_u}{d\tau_{ju}}\right) + D_{iu}\cdot\frac{dp_u}{d\tau_{ju}}\right] + \frac{w_j D_{ju}}{|I|} + D_n\frac{dp_n}{d\tau_{ju}} \frac{dD_n}{d\tau_{ju}}\cdot(p_n - c + \phi - \phi_n) + \frac{dD_u}{d\tau_{ju}}(\phi) - \frac{D_{ju}}{|I|} - \frac{1}{|I|}\sum_i\left[\frac{dD_{in}}{d\tau_{ju}}\tau_{in} + \frac{dD_{iu}}{d\tau_{ju}}\tau_{iu}\right]. \tag{65}$$

The simplification of the subsidy terms will be slightly different, but we get

$$\begin{aligned}\frac{dD_n}{d\tau_{ju}}(p_n - c + \phi - \phi_n - \bar{\tau}_n) + \frac{dD_u}{d\tau_{ju}}(\phi - \bar{\tau}_u) + \frac{D'_c}{|I|}(\tau_{jn} - \bar{\tau}_n) + \frac{D'_u}{|I|}(\tau_{ju} - \bar{\tau}_u) = \\ (1 - w_j)\frac{D_{ju}}{|I|} + b_n\frac{dp_n}{d\tau_{ju}} + \frac{dp_u}{d\tau_{ju}}(b_u - (1-g)b_n).\end{aligned} \tag{66}$$

Note that if we were to sum equations (64) and (66) $\forall j \in I$, they would evaluate to the same FOC equations (39) and (40) in the uniform subsidy case. This implies that the mathematical expressions for $\bar{\tau}_n$ and $\bar{\tau}_u$ are given in equations (48) and (49), respectively.

Let $A = \frac{b_n D'_u - b_u D'_c}{D'_n D'_u - D'^2_c}$ and $B = \frac{b_n D'_c - b_u D'_n}{D'_n D'_u - D'^2_c}$. Note that $AD'_n - BD'_c = b_n$ and $AD'_c - BD'_u = b_u$. Using this, we get

$$\begin{aligned}
-A\frac{dD_n}{d\tau_{jn}} + B\frac{dD_u}{d\tau_{jn}} &= -A\left[D'_n\left(\frac{dp_n}{d\tau_{jn}} - \frac{1}{|I|} - (1-g)\frac{dp_u}{d\tau_{jn}}\right) + D'_c\frac{dp_u}{d\tau_{jn}}\right] \\
&\quad + B\left[D'_c\left(\frac{dp_n}{d\tau_{jn}} - \frac{1}{|I|} - (1-g)\frac{dp_u}{d\tau_{jn}}\right) + D'_u\frac{dp_u}{d\tau_{jn}}\right] \\
&= -b_n\left[\frac{dp_n}{d\tau_{jn}} - \frac{1}{|I|} - (1-g)\frac{dp_u}{d\tau_{jn}}\right] - b_u\frac{dp_u}{d\tau_{jn}} \\
&= -b_n\frac{dp_n}{d\tau_{jn}} + \frac{b_n}{|I|} + \frac{dp_u}{d\tau_{jn}}((1-g)b_n - b_u) \qquad (67) \\
-A\frac{dD_n}{d\tau_{ju}} + B\frac{dD_u}{d\tau_{ju}} &= -b_n\left[\frac{dp_n}{d\tau_{ju}} - (1-g)\frac{dp_u}{d\tau_{ju}}\right] - b_u\left[\frac{dp_u}{d\tau_{ju}} - \frac{1}{|I|}\right] \\
&= -b_n\frac{dp_n}{d\tau_{ju}} + \frac{dp_u}{d\tau_{ju}}((1-g)b_n - b_u) + b_u\frac{1}{|I|}. \qquad (68)
\end{aligned}$$

Plugging in these simplifications, we can simplify equations (64) and (66) as

$$\begin{aligned}
\frac{D'_n(\tau_{jn} - \bar{\tau}_n) + D'_c(\tau_{ju} - \bar{\tau}_u)}{|I|} &= -\frac{dD_n}{d\tau_{jn}}A + \frac{dD_u}{d\tau_{jn}}B + (1-w_j)\frac{D_{jn}}{|I|} + b_n\frac{dp_n}{d\tau_{jn}} + \frac{dp_u}{d\tau_{jn}}(b_u - (1-g)b_n) \\
&= (1-w_j)\frac{D_{jn}}{|I|} + \frac{b_n}{|I|} \qquad (69) \\
\frac{D'_c(\tau_{jn} - \bar{\tau}_n) + D'_u(\tau_{ju} - \bar{\tau}_u)}{|I|} &= -\frac{dD_n}{d\tau_{ju}}A + \frac{dD_u}{d\tau_{ju}}B + (1-w_j)\frac{D_{ju}}{|I|} + b_n\frac{dp_n}{d\tau_{ju}} + \frac{dp_u}{d\tau_{ju}}(b_u - (1-g)b_n) \\
&= (1-w_j)\frac{D_{ju}}{|I|} + \frac{b_u}{|I|}. \qquad (70)
\end{aligned}$$

This can be written as

$$\begin{bmatrix} D'_n & D'_c \\ D'_c & D'_u \end{bmatrix}\begin{bmatrix} (\tau_{jn} - \bar{\tau}_n) \\ (\tau_{ju} - \bar{\tau}_u) \end{bmatrix} = \begin{bmatrix} (1-w_j)D_{jn} + b_n \\ (1-w_j)D_{ju} + b_u \end{bmatrix}. \qquad (71)$$

By assumption, the matrix of demand slopes can be inverted so

$$\tau_{jn} - \bar{\tau}_n = \frac{D'_u \cdot ((1-w_j)D_{jn} + b_n) - D'_c \cdot ((1-w_j)D_{ju} + b_u)}{D'_n D'_u - {D'_c}^2} = \frac{(1-w_j)(D'_u D_{jn} - D'_c D_{ju}) + D'_u b_n - D'_c b_u}{D'_n D'_u - {D'_c}^2} \tag{72}$$

$$\tau_{ju} - \bar{\tau}_u = \frac{-D'_c((1-w_j)D_{jn} + b_n) + D'_n((1-w_j)D_{ju} + b_u)}{D'_n D'_u - {D'_c}^2} = \frac{(1-w_j)(D'_n D_{ju} - D'_c D_{jn}) + D'_n b_u - D'_c b_n}{D'_n D'_u - {D'_c}^2} \tag{73}$$

Substituting back again for $\bar{\tau}_u$ and $\bar{\tau}_n$, we get

$$\begin{aligned} \tau^*_{jn} &= p_n - c + \phi - \phi_n \quad + \frac{(1-w_j)\cdot(D'_u D_{jn} - D_{ju} D'_c)}{D'_n D'_u - {D'_c}^2} \\ \tau^*_{ju} &= \phi \qquad\qquad\qquad\quad + \frac{(1-w_j)\cdot(D'_n D_{ju} - D_{jn} D'_c)}{D'_n D'_u - {D'_c}^2}. \end{aligned} \tag{74}$$

These optimal subsidies decrease smoothly with income if demand and welfare weights are smooth in income.

B.7 Proof of Proposition 4

The section uses two additional assumptions. First, we assume the lower-income individuals are less likely to buy new EVs (lower per-capita new EV demand) and thus $(1-g)D^L_n < D^L_u$ for the aggregate low-income group L. Formally we also require that $(1-g)Cov(w_i, D_{in}) \leq Cov(w_i, D_{iu})$ (and $Cov(w_i, D_{in}) < 0$), meaning used EVs are relatively less associated with high-income than new EVs (but could still be positively correlated). Second, we assume the covariance between w_i and $\frac{D_{in}}{D^L_n} - \frac{D_{iu}}{D^L_u}$ is sufficiently small in absolute value within the low-income types. This precludes the case where relatively rich people in the low-income group are much more likely to buy new EVs. We assume the total EV lifetime externality plus markup $p_n - c + (2-g)\phi - \phi_n$ is strictly positive.

In our main setup, we assumed that all consumers are at interior solutions (i.e., they purchase strictly positive quantities of new and used EVs). This will be a key assumption in this proof and implies that the subsidy level will enter r_n and r_u with a common factor μ defined as the share of eligible consumers. Therefore, we can use all pass-through rates and demand derivatives from Appendix B.1 which were derived with a constant μ across markets.

Let L denote the set of income types that are eligible and F for full eligibility. Let $\mu_e = \sum_{i \in L} 1/|I|$ denote the eligible consumer share.

Our goal is to evaluate expressions of the form $M^e_a := \frac{d(W+G)/d\tau^e_a}{dG/d\tau^e_a}$ for $e \in \{L, F\}$, where we explicitly evaluate the derivatives at $\tau_n = \tau_u = 0$. This implies that $\frac{dG}{d\tau^e_a} = D^e_a = \sum_{i \in e} \frac{D_{ia}}{|I|}$ which is the eligible demand for that age.

We can express

$$W + G = \sum_i \frac{w_i CS_i}{|I|} + D_n \cdot (p_n - c + \phi - \phi_n) + \phi D_u. \tag{75}$$

Define $b_a = Cov(w_i, D_{ia}) = \frac{\sum_i w_i D_{ia}}{|I|} - D_a$ as in previous subsections. Differentiating gives

$$\begin{aligned}\frac{d(W+G)}{d\tau_n^e} &= -\sum_i \frac{w_i}{|I|}\left[D_{in}\left(\frac{dp_n}{d\tau_n^e} - \mathbb{1}\{i \in e\} - (1-g)\frac{dp_u}{d\tau_n^e}\right) + D_{iu}\frac{dp_u}{d\tau_n^e}\right] + \\ &\quad \frac{dD_n}{d\tau_n^e} \cdot (p_n - c + \phi - \phi_n) + D_n\left(\frac{dp_n}{d\tau_n^e}\right) + \phi\frac{dD_u}{d\tau_n^e} \\ &= \sum_{i\in e} \frac{w_i D_{in}}{|I|} - b_n\frac{dp_n}{d\tau_n^e} + \frac{dp_u}{d\tau_n^e}((1-g)b_n - b_u) + \frac{dD_n}{d\tau_n^e}(p_n - c + \phi - \phi_n) + \phi\frac{dD_u}{d\tau_n^e} \end{aligned} \tag{76}$$

and

$$\begin{aligned}\frac{d(W+G)}{d\tau_u^e} &= -\sum_i \frac{w_i}{|I|}\left[D_{in}\left(\frac{dp_n}{d\tau_u^e} - (1-g)\frac{dp_u}{d\tau_u^e}\right) + D_{iu}\left(\frac{dp_u}{d\tau_u^e} - \mathbb{1}\{i \in e\}\right)\right] + \\ &\quad \frac{dD_n}{d\tau_u^e} \cdot (p_n - c + \phi - \phi_n) + D_n\left(\frac{dp_n}{d\tau_u^e}\right) + \phi\frac{dD_u}{d\tau_u^e} \\ &= \sum_{i\in e} \frac{w_i D_{iu}}{|I|} - b_n\frac{dp_n}{d\tau_u^e} + \frac{dp_u}{d\tau_u^e}((1-g)b_n - b_u) + \frac{dD_n}{d\tau_u^e}(p_n - c + \phi - \phi_n) + \phi\frac{dD_u}{d\tau_u^e}. \end{aligned} \tag{77}$$

Our proof strategy is to first suppose that $g' = 0$. We will show that under no eligibility conditions new and used subsidies are equivalent ($M_n^F = M_u^F$). Then we will show that restricted new subsidies are preferred to unrestricted new subsidies ($M_n^L > M_n^F$) and finally that restricted new subsidies are preferred to restricted used subsidies ($M_n^L > M_u^L$).

Let $C = p_n - c + (2-g)\phi - \phi_n$ for notational simplicity.

Starting with the full eligibility, we can express

$$\frac{d(W+G)}{d\tau_n} = \frac{dD_n}{d\tau_n}(p_n - c + (2-g)\phi - \phi_n) - b_n\frac{dr_n}{d\tau_n} - b_u\frac{dr_u}{d\tau_n} + D_n \tag{78}$$

$$= \left[D_n'\frac{dr_n}{d\tau_n} + D_c'\frac{dr_u}{d\tau_n}\right](p_n - c + (2-g)\phi - \phi_n) - b_n\frac{dr_n}{d\tau_n} - b_u\frac{dr_u}{d\tau_n} + D_n \tag{79}$$

$$= \frac{1}{1-g}\left(\left[D_n'\frac{dr_n}{d\tau_u} + D_c'\frac{dr_u}{d\tau_u}\right](p_n - c + (2-g)\phi - \phi_n) - b_n\frac{dr_n}{d\tau_u} - b_u\frac{dr_u}{d\tau_u} + D_u\right) \tag{80}$$

$$= \frac{1}{1-g}\frac{d(W+G)}{d\tau_u}, \tag{81}$$

where we use the clause in Proposition 1 that when $g' = 0$, $(1-g)\frac{dr_a}{d\tau_n} = \frac{dr_a}{d\tau_u}$.

Thus

$$M_n^F = \frac{d(W+G)/d\tau_n}{dG/d\tau_n} = \frac{d(W+G)/d\tau_u}{(1-g)D_n} = \frac{d(W+G)/d\tau_u}{dG/d\tau_u} = M_u^F. \tag{82}$$

Comparing restricted and unrestricted new subsidies. Since eligibility enters linearly in prices and thus demand, as mentioned above, $\mu_e \frac{dD_n}{d\tau_n} = \frac{dD_n}{d\tau_n^e}$ We can compute

$$\begin{aligned} M_n^L - M_n^F &= \frac{\mu_e \left[\frac{dD_n}{d\tau_n} C - b_n \frac{dp_n}{d\tau_n} + \frac{dp_u}{d\tau_n}((1-g)b_n - b_u)\right] + \sum_{i\in L} \frac{w_i D_{in}}{|I|}}{D_n^L} \\ &\quad - \frac{\frac{dD_n}{d\tau_n} C + \sum_i \frac{w_i D_{in}}{|I|} - b_n \frac{dp_n}{d\tau_n} + \frac{dp_u}{d\tau_n}((1-g)b_n - b_u)}{D_n} \\ &= \left[\frac{dD_n}{d\tau_n} C - b_n \frac{dp_n}{d\tau_n} + \frac{dp_u}{d\tau_n}((1-g)b_n - b_u)\right] \cdot \left(\frac{\mu_e}{D_n^L} - \frac{1}{D_n}\right) + \frac{\sum_{i\in L} w_i D_{in}}{D_n^L |I|} - \frac{\sum_i w_i D_{in}}{D_n |I|}. \end{aligned} \tag{83}$$

First, low-income groups have less new EV demand per person, so $\mu_e / D_n^L = 1/(D_n^L/\mu_e) > 1/D_n$. Second, using pass-through results from Appendix B.1 and our assumption that $(1-g)b_n \leq b_u$ and $b_n < 0$ implies that $\frac{dp_u}{d\tau_n}\left[(1-g)b_n - b_u\right] \geq 0$ and $-b_n \frac{dp_n}{d\tau_n} \geq 0$. Third, for the summation terms, the low group has higher welfare weights w_i than the high-income group, so the demand-weighted average is also higher. Thus the summation terms are positive.

Given $\frac{dD_n}{d\tau_n} C > 0$, this shows that $M_n^L - M_n^F > 0$.

Comparing restricted new and used subsidies.

$$\begin{aligned} M_n^L - M_u^L = &\frac{\mu_e \left[\frac{dD_n}{d\tau_n} C - b_n \frac{dp_n}{d\tau_n} + \frac{dp_u}{d\tau_n}((1-g)b_n - b_u)\right] + \sum_{i\in L} \frac{w_i D_{in}}{|I|}}{D_n^L} - \\ &\frac{\mu_e \left[\frac{dD_n}{d\tau_u} C - b_n \frac{dp_n}{d\tau_u} + \frac{dp_u}{d\tau_u}((1-g)b_n - b_u)\right] + \sum_{i\in L} \frac{w_i D_{iu}}{|I|}}{D_u^L}. \end{aligned} \tag{84}$$

Note that our assumption $(1-g)D_n^L < D_u^L$ implies $\frac{1}{D_n^L} > \frac{1-g}{D_u^L}$, thus

$$\begin{aligned} M_n^L - M_u^L > \frac{\mu_e}{D_u^L} \Bigg[& b_n \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_n}{d\tau_n}\right) + \left[(1-g)b_n - b_u\right] \left((1-g)\frac{dp_u}{d\tau_n} - \frac{dp_u}{d\tau_u}\right) \\ & + C\left((1-g)\frac{dD_n}{d\tau_n} - \frac{dD_n}{d\tau_u}\right)\Bigg] \\ & + \sum_{i\in L} \frac{w_i}{|I|}\left(\frac{D_{in}}{D_n^L} - \frac{D_{iu}}{D_u^L}\right). \end{aligned} \tag{85}$$

For the first two lines, by the results in Appendix B.1 $(1-g)\frac{dp_n}{d\tau_n} \geq \frac{dp_n}{d\tau_u} \geq 0$ and $b_n < 0$, so the first term is weakly positive. For the second term, $\frac{dp_u}{d\tau_n} \leq 0$, $\frac{dp_u}{d\tau_u} \geq 0$, and $(1-g)b_n - b_u \leq 0$ by assumption, so the whole term is weakly positive. For the third term, $(1-g)\frac{dD_n}{d\tau_n} - \frac{dD_n}{d\tau_u} = \frac{-D'_n}{\theta}\left[(1-g)\frac{dp_n}{d\tau_n} - \frac{dp_n}{d\tau_u}\right] > 0$ by the same rationale as term one. Therefore, on net the these lines are weakly positive.

Note that for the third line w_i can be replaced with $w_i - \bar{w}_L$, meaning this term is the covariance between weights and relative new EV demand within the low-income group. This could be negative, but in our setup we constrained this term to be "small enough" in absolute value, we use this here to assume that in aggregate equation (85) implies $M_n^L > M_u^L$.

To conclude, note that the formulas given for M_a^e are functions of equilibrium demand/price derivatives and primitives. Given our linear structure, these derivatives are continuous in g'. Thus, there exists $\bar{g}'_i > 0$ for each of the three MVPF inequalities such that if $|g'| < \bar{g}'_i$, then the strict inequalities hold. Taking the $\overline{g}$ as the minimum of these $\bar{g}'_i$ gives the interval of possible values $g' \in [-\overline{g}, 0]$ where the proposition is valid.

B.8 Short-Run Effects

All of the previous theory sections focused on steady-state effects. However, the IRA EV tax credits were a surprise policy change, taking effect with effectively no opportunity for used vehicle supply to adjust. To model this, we consider a surprise subsidy announced at the beginning of period t, with period $t-1$ new vehicle quantity fixed.

Transaction price limits were another key feature of the IRA. To incorporate this, we now extend our model to incorporate quality differentiation in the used EV market. We allow for a low-quality and high-quality used good, with demand denoted D_u^L and D_u^H, respectively. We think of the low-quality used good as used EVs that would be priced below the $25,000 price limit, and the high-quality used good as used EVs that would be priced above the $25,000 price limit. This allows a representation, albeit imperfect, of the upward price shift from the used EV tax credit that we would expect to estimate in Section 5.

We assume demand for all three goods are functions of all rents: $D_a := D_a(r_n, r_u^L, r_u^H)$. Furthermore, let $D'_q := \frac{dD_u^q}{dr_u^q} < 0$ for $q \in \{L, H, n\}$ and assume own-price effects dominate the corresponding cross-price effects. We denote the cross effects $D'_{nL} := \frac{dD_n}{dr_u^L} = \frac{dD_u^L}{dr_n}$, $D'_{nH} := \frac{dD_n}{dr_u^H} = \frac{dD_u^H}{dr_n}$, and $D'_{LH} := \frac{dD_u^L}{dr_u^H} = \frac{dD_u^H}{dr_u^L}$. We assume all three market demands are linear in rents.

Proposition 5 presents a key result motivating our bunching estimator in Section 5.

Proposition 5. *Assume $g' = 0$ and $D'_{nL} = D'_{nH} = 0$. Then the effect of a surprise subsidy τ_{ut} announced*

at the beginning of period t where only low-quality used EVs are eligible is

$$\Delta p_{ut}^{L} = \mu\tau_{ut},$$
$$\Delta p_{ut}^{H} = 0.$$

Proof: see Appendix B.8.1.

Proposition 5 states that if used EV supply (net of scrappage) of each quality is fully inelastic and there is no new-used substitution, then the low-quality used vehicle price increases one-for-one with the subsidy, after adjusting for the share of consumers μ that are eligible.

The price effects given in the proposition imply a sorting of consumers based on eligibility. Ineligible consumers will face a higher rental price in the low-quality used market and will thus substitute to high-quality used EVs. The reverse is true for eligible groups. The proposition states that this sorting does not imply some of the incidence is shifted to the high-quality market.

B.8.1 Proof of Proposition 5

We will consider the effect of a used subsidy with income limits that is also price limited at $\bar{p}$. We assume μ fraction of consumers are income-eligible and a starting equilibrium such that $p_u^L < \bar{p} < p_u^H$, which implies only low-quality used EVs are eligible. Additionally, we consider consumers with identical demand slopes purchasing strictly positive quantities of all goods (interior solutions) so τ_u will enter aggregate demand for D_u^L by the eligibility share μ.

Let S_u^L and S_u^H be the exogenous supply of low- and high-quality used EVs. Our short-run equilibrium is characterized by firm profit-maximization and market clearing in the low- and high-quality used EV markets. These three equations are defined as follows,

$$p_{nt} - c = \frac{-\theta}{D_n'} D_n(p_{nt} - \tilde{v}_{t+1}(\tilde{p}_{u,t+1}), p_{ut}^L - \mu\tau_{ut} - v^s, p_{ut}^H - v^s) \tag{86}$$
$$(1-g_t)S_u^L = D_u^L(p_{nt} - \tilde{v}_{t+1}(\tilde{p}_{u,t+1}), p_{ut}^L - \mu\tau_{ut} - v^s, p_{ut}^H - v^s) \tag{87}$$
$$(1-g_t)S_u^H = D_u^H(p_{nt} - \tilde{v}_{t+1}(\tilde{p}_{u,t+1}), p_{ut}^L - \mu\tau_{ut} - v^s, p_{ut}^H - v^s). \tag{88}$$

We drop the subscript t for the current period. Note that $\tilde{g}_{t+1}$ and $\frac{d\tilde{p}_{u,t+1}}{d\tau_u}$ are consumers' expectations and are indeterminate within our model because the market may not equilibrate in one period.

Differentiating, we get the firm profit-maximizing first-order condition and two necessary conditions given by market-clearing:

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1-\tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u}\right] + D'_{nL}\left[\frac{dp_u^L}{d\tau_u} - \mu\right] + D'_{nH}\frac{dp_u^H}{d\tau_u}\right) \tag{89}$$

$$-g'\frac{dp_u^L}{d\tau_u}S_u^L = D'_{nL}\left[\frac{dp_n}{d\tau_u} - (1-\tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u}\right] + D'_L\left[\frac{dp_u^L}{d\tau_u} - \mu\right] + D'_{LH}\frac{dp_u^H}{d\tau_u} \tag{90}$$

$$-g'\frac{dp_u^H}{d\tau_u}S_u^H = D'_{nH}\left[\frac{dp_n}{d\tau_u} - (1-\tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u}\right] + D'_{LH}\left[\frac{dp_u^L}{d\tau_u} - \mu\right] + D'_H\frac{dp_u^H}{d\tau_u}. \tag{91}$$

Define $\tilde{D}_H = D'_H + g'S_u^H$ and $\tilde{D}_L = D'_L + g'S_u^L$, which is the net coefficient on own-price derivatives in the EV markets. For conciseness, also denote $\frac{d\tilde{r}_n}{d\tau_u} = \frac{dp_n}{d\tau_u} - (1-\tilde{g}_{t+1})\frac{d\tilde{p}_{t+1}}{d\tau_u}$.

Rewrite the used market clearing conditions as

$$\tilde{D}_L\frac{dp_u^L}{d\tau_u} + D'_{LH}\frac{dp_u^H}{d\tau_u} = \mu D'_L - D'_{nL}\frac{d\tilde{r}_n}{d\tau_u} \tag{92}$$

$$D'_{LH}\frac{dp_u^L}{d\tau_u} + \tilde{D}_H\frac{dp_u^H}{d\tau_u} = \mu D'_{LH} - D'_{nH}\frac{d\tilde{r}_n}{d\tau_u}. \tag{93}$$

Let $\chi_{SR} = \tilde{D}_L\tilde{D}_H - (D'_{LH})^2$, then by using Cramer's rule the used market price effects are given by

$$\begin{aligned}\frac{dp_u^L}{d\tau_u} &= \frac{\tilde{D}_H\left(\mu D'_L - D'_{nL}\frac{d\tilde{r}_n}{d\tau_u}\right) - D'_{LH}\left(\mu D'_{LH} - D'_{nH}\frac{d\tilde{r}_n}{d\tau_u}\right)}{\chi_{SR}} \\ &= \mu\frac{\tilde{D}_H D'_L - (D'_{LH})^2}{\chi_{SR}} - \frac{d\tilde{r}_n}{d\tau_u}\cdot\frac{\tilde{D}_H D'_{nL} - D'_{LH}D'_{nH}}{\chi_{SR}}\end{aligned} \tag{94}$$

$$\begin{aligned}\frac{dp_u^H}{d\tau_u} &= \frac{\tilde{D}_L\left(\mu D'_{LH} - D'_{nH}\frac{d\tilde{r}_n}{d\tau_u}\right) - D'_{LH}\left(\mu D'_L - D'_{nL}\frac{d\tilde{r}_n}{d\tau_u}\right)}{\chi_{SR}} \\ &= \mu\frac{D'_{LH}g'S_u^L}{\chi_{SR}} - \frac{d\tilde{r}_n}{d\tau_u}\cdot\frac{\tilde{D}_L D'_{nH} - D'_{LH}D'_{nL}}{\chi_{SR}}.\end{aligned} \tag{95}$$

If we assume there are no substitution effects from either used EV market into the new market ($D'_{nH} = D'_{nL} = 0$), then as scrappage becomes perfectly inelastic ($g' \to 0$), the price derivatives converge to $\frac{dp_u^L}{d\tau_u} \to \mu$ and $\frac{dp_u^H}{d\tau_u} \to 0$.

We now look at the individual rent effects by consumer group under these assumptions. For ineligible consumers, low-quality EV demand changes by $\mu D'_L < 0$, while high-quality EV demand changes by $\mu D'_{LH} > 0$. Since supply is fully inelastic, the demand change of the eligible group must be the negative of the ineligible group. This implies that eligible buyers sorted into the low-quality market and ineligible consumers moved into the high-quality market.

C Data Appendix

This section provides data preparation details.

For the structural model, we take several steps to reduce the size of the choice set. First, we group brands that are no longer selling new cars and have fewer than one million registrations in Q3 2023 into a larger make under the same firm, or absent that, into an "Other" category. This leaves 28 brands. Second, we drop gas-only car types with fewer than 35,000 total registrations or fewer than 5,000 per available model year in Q3 2023. Analogously, we drop hybrids, plug-in hybrids, and electric-only vehicles with fewer than 1,500 total registrations or fewer than 300 per model year. Third, we drop any car type that was available for fewer than three model years and was not available for model year 2023. Fourth, we drop jy observations in the first and/or last model year that a car type is available if the stock in those model years is especially low.

We use transaction data from October 2022 through September 2023 to roughly correspond to the months when the 2023 model year is sold. However, some new model year 2023 vehicles are sold outside that window, which would bias our new vehicle market size downwards. Therefore, we code any transactions that Experian classifies as "new" as age=0 (model year 2023), regardless of the observed model year. Similarly, we also label any model year 2023 transactions Experian labels as "used" to be age=1 (model year 2022).

Table A1 column 1 shows the total new sales observed over the course of our sample period 10/2022 – 9/2023 in the raw Experian data and the remaining count after each of our cleaning steps defined above and in Section 4 of the main body. Column 2 presents the analogous values for total vehicle registrations as of the end of Q3 2022.

Table A1: **Transaction and Stock Count by Data Cleaning Step**

	(1) 2023 new vehicle sales (millions)	(2) End Q3 2022 stock (millions)
All Experian data	14.76	282.38
Remove model year < 2004	14.76	235.75
Remove makes over $200k	14.74	235.61
Remove sports cars	14.35	228.44
Remove nonstandard fuel types	14.07	226.01
Remove full-sized vans	13.75	221.77
Remove heavy-duty vehicles	13.29	212.60
Remove uncommon models	13.26	212.46
Final total individuals	10.78	200.71
Final total fleets	2.48	11.74

Notes: Column 1 shows the total new sales in the Experian data over the course of 10/2022 – 9/2023 after each cleaning step. Column 2 shows the total registration count at the end of Q3 2022. We define “makes over $200k" based on the average new vehicle sales price from our Cox data.

D Bunching Estimator Appendix

D.1 Bunching Model Setup

Formally, we model that tax credits affect latent prices as described in the equation below.

$$\begin{aligned}
p_0^L < \underline{p} - \rho\tau_u &\implies p_1^L = p_0^L + \rho\tau_u \\
\underline{p} - \rho\tau_u \leq p_L^0 \leq p^* &\implies \underline{p} \leq p_1^L \leq p^* \\
p^* < p_L^0 < \overline{p} &\implies \underline{p} \leq p_1^L \leq p^* \text{ with probability } d,\ p_1^L = p_0^L \text{ with probability } 1-d \\
\overline{p} \leq p_0^L &\implies p_1^L = p_0^L.
\end{aligned} \tag{96}$$

D.2 Bunching Estimation Strategy

This appendix provides details on the bunching estimation strategy. For empirical implementation, we assume that the distributions are piecewise uniform in bins from $[x],001 to $[x+1],000. We define $b \in \mathcal{B}$ as a set of bin midpoints and l_{Tb} as the latent density of the bin with midpoint b in scenario T.

Steps 1 and 3: Estimating Left-Digit Effects

We assume that the left-digit effect function Λ shifts share $\overline{\lambda}_k$ down from the $1000 bin just above a round number price with left digit $k \in \{5, 10\}$, and shifts share $\underline{\lambda}_k$ up from the $1000 bin below. For example, the $b = 34$ bin is just below $35,000, and it draws some mass down from the $b = 35$ bin and some mass up from the $b = 33$ bin: $f_1(34) = l_1(34) + \overline{\lambda}_5 l_1(35) + \underline{\lambda}_5 l_1(33)$.

Define $m_5(b)$ and $m_{10}(b)$ as indicators whether the thousands place in bin b is a multiple of 5 or 10, respectively. In full generality, left digit effect on densities is

$$f_T(b) = \Lambda(l_T) = l_T(b) + \sum_{k\in\{5,10\}} \Bigg[\underbrace{-m_k(b+2)\cdot \underline{\lambda}_k l_T(b)}_{\text{upward shift from below}} + \underbrace{m_k(b+1)\cdot\left(\underline{\lambda}_k l_T(b-1) + \overline{\lambda}_k l_T(b+1)\right)}_{\text{excess mass}} - \underbrace{m_k(b)\cdot\overline{\lambda}_k l_T(b)}_{\text{downward shift from above}} \Bigg]. \tag{97}$$

To estimate the left-digit effects Λ, we assume the latent distribution follows local quadratic fits and then solve for Λ to most closely match f_1. Specifically, we allow separate quadratic fits over $5,000 intervals, where the middle bins are $n \in \{9, 14, \ldots, 69\}$. Let $h(b_{nt}) \coloneqq \beta_{0nt} + \beta_{1nt} b_n + \beta_{2nt} b_n^2$ denote the quadratic fit for bin b with central bin number n and month t. We let the quadratic fit vary by month to allow for changes in the distribution of vehicle prices. We estimate the following

$$f_1(b_n) = h(b_n) + \sum_k m_k(b_n+1)\cdot(\underline{\lambda}_k h(b_n-1) + \overline{\lambda}_k h(b_n+1)) - m_k(b_n+2)\cdot\underline{\lambda}_k h(b_n) - m_k(b_n)\cdot\overline{\lambda}_k h(b_n) \tag{98}$$

with non-linear least squares, using data from all months from 2022–2025.

Table A2 presents results, where column 1 reports the unrestricted λ coefficients using only GVs. We estimate $\underline{\lambda}_5 = -0.005, \overline{\lambda}_5 = 0.023$ for the $5,000 multiples, and an additional $\underline{\lambda}_{10} = 0.002, \overline{\lambda}_{10} = 0.061$ for the $10,000 multiples. Thus, as might be expected, most bunching is downward from above the round numbers (not upward toward the round numbers), and there is additional bunching below the $10,000 multiples relative to the $5,000 multiples.

Given the small and sometimes negative values of the upwards bunching probabilities, in the main estimation we restrict $\underline{\lambda}_5 = \underline{\lambda}_{10} = 0$ and use the values from Table A2 column 2. In column 2, we estimate

Table A2: Λ **Left-Digit Effect Estimates**

	GVs		EVs	
	(1)	(2)	(3)	(4)
$\overline{\lambda}_5$	0.023	0.020	0.020	0.017
	(0.001)	(0.001)	(0.005)	(0.004)
$\overline{\lambda}_{10}$	0.061	0.062	0.063	0.066
	(0.001)	(0.001)	(0.006)	(0.005)
$\underline{\lambda}_5$	-0.005		-0.007	
	(0.001)		(0.005)	
$\underline{\lambda}_{10}$	0.002		0.005	
	(0.001)		(0.006)	
Observations	3,120	3,120	4,000	4,000

Notes: This table shows the resulting Λ values from estimating equation (98) using only GV transactions in columns 1–2 and only EV transactions in columns 3–4. We restrict $\underline{\lambda}_5 = \underline{\lambda}_{10} = 0$ in columns 2 and 4.

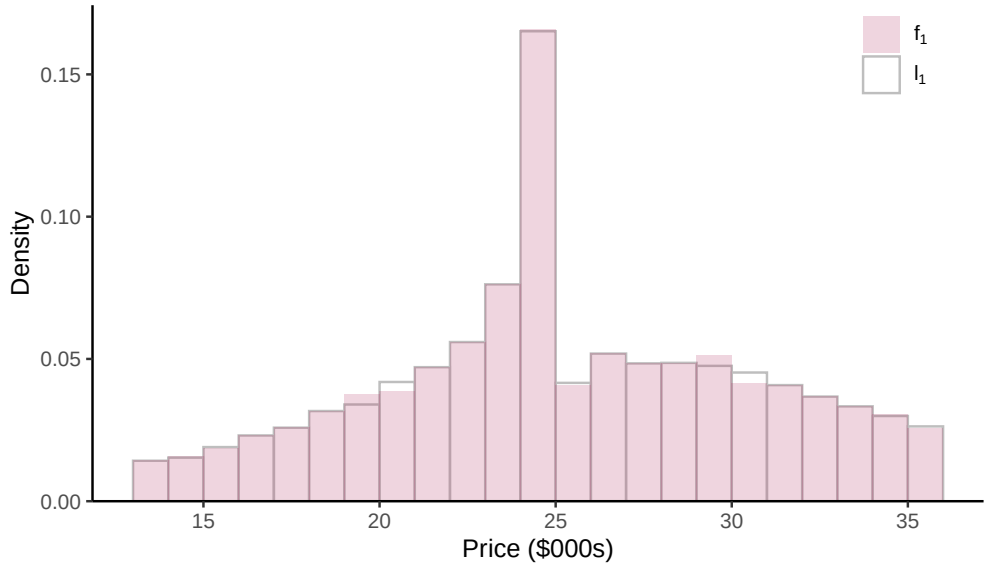
that about 2.0 percent of mass in the bin just above multiples of \$5,000 shifts to the bin just below, and an additional 6.2 percent of mass in the bin just above multiples of \$10,000 shifts to the bin just below.

While we prefer the GV estimated Λ values due to the significantly increased transaction counts, there is a potential concern that EVs could exhibit different left-digit behavior. To test this, columns 3 and 4 of Table A2 present the results using only EVs. To avoid used EV subsidy related bunching, we exclude the \$5,000 bin interval covering \$22,000–\$27,000 for years 2023–2025. The observation count for these columns is larger because we include central bins up to \$99,000, as EVs can be more expensive. The EV and GV results are similar. Comparing the restricted models in columns 2 versus 4, switching to EVs causes $\overline{\lambda}_5$ to change slightly from 0.020 to 0.017 and $\overline{\lambda}_{10}$ from 0.062 to 0.066.

We apply the estimated Λ values to our estimation of $\widehat{\rho\tau_u}$ by converting between the actual price distributions f_T and the latent distributions l_T. To estimate the latent with-subsidy density l_1, we insert the λ parameters into the inverse of equation (97). Figure A2 presents the estimated l_1 for the 2024+ distribution, showing a bit more mass just above round numbers compared to f_1.

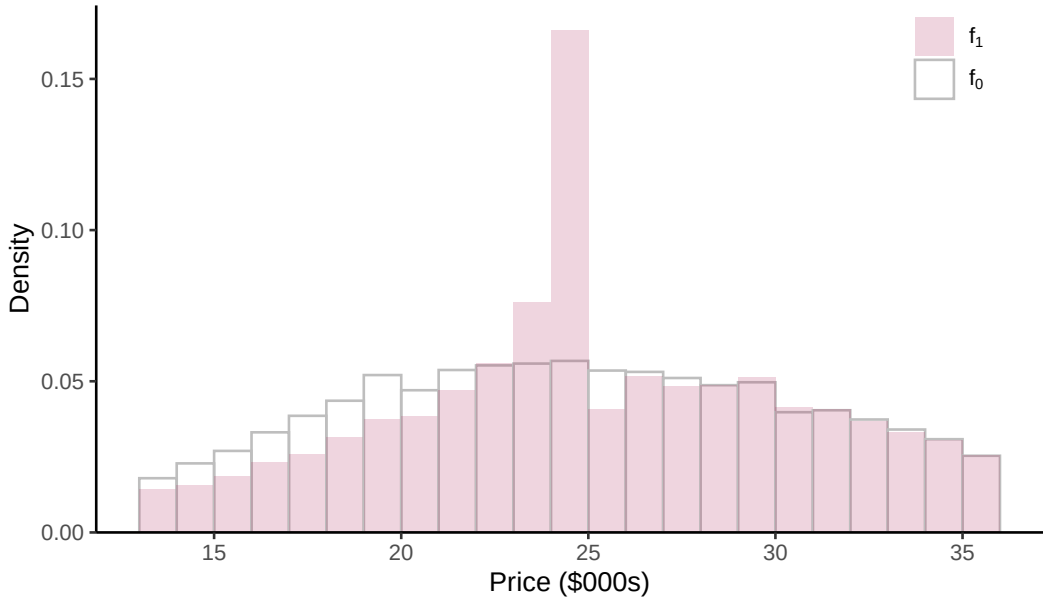
After estimating the latent counterfactual density l_0 via regression in step 2 (as described below), we reconstruct the counterfactual density f_0 in step 3. To do this, we simply apply equation (97). Figure A3 plots the results of the full procedure, showing the observed price density f_1 in maroon and the predicted counterfactual density f_0 in grey. Notice that since the density is generally increasing between \$13,000 and \$23,000, when we recognize that the tax credit shifts the distribution to the right, f_0 has higher density than f_1 at each point in that range.

Figure A2: **Equilibrium and Latent Factual Distributions**



Notes: This figure presents the binned latent price distribution l_1 for 2024+ after applying the left digit effects Λ from column 1 of Table A2 to the observed EV price distribution f_1.

Figure A3: **Actual and Counterfactual Price Distributions**



Notes: f_1 is the observed with-subsidy transaction price density function for EVs over 2024+. f_0 is the result of solving for the latent counterfactual l_0 via regression and then applying left digit effects Λ.

Step 2: Estimating the Price Shift

We first describe the polynomial fit to l_0, conditional on a candidate value of $\rho\tau_u$. To ensure that the polynomial fits well near the bunching region, we only use bins from \$13,001 to \$36,000. Our primary estimates use a polynomial of order $K = 5$. Define $\mathcal{B}_E$ as the set of three bins in an "excluded region" from $\underline{p} =$ \$23,001 to $\overline{p} =$ \$26,000. We include dummy variables for these bins to ensure that the excluded region does not contribute to identifying the polynomial. The polynomial fit is

$$l_{1b} = \sum_{k=0}^{K} \left(\beta_k \left[b - \underbrace{(\rho\tau_u)\mathbb{1}(b \leq p^*)}_{\text{price shift}} \right]^k \right) + \sum_{i \in \mathcal{B}_E} \gamma_i \mathbb{1}(b = i) + \epsilon_b. \tag{99}$$

The "price shift" term accounts for how the tax credit shifts l_1 upward relative to l_0. Thus, even though we use data from l_1, the polynomial fit is the no-subsidy density $\hat{l}_0$, not the upward-shifted with-subsidy density $\hat{l}_1$.

Define $\hat{L}_0(p|\rho\tau_u)$ as the cumulative density implied by evaluating the fitted polynomial $\hat{l}_1$ at the bin midpoints $\mathcal{B}$ and assuming bin uniformity. For example, if $p =$ \$23,200, $\hat{L}_0(p|\rho\tau_u) = \hat{L}_0(23|\rho\tau_u) + 0.2 \cdot \hat{l}_1(23.5|\rho\tau_u)$. We search for the $\widehat{\rho\tau_u}$ such that $\hat{L}_0(\bar{p}|\rho\tau_u) - \hat{L}_0(\underline{p} - \rho\tau_u|\rho\tau_u)$ satisfies mass equivalence.

Our approach is broadly inspired by Kleven and Waseem (2013), but we deviate in two ways. First, our regression in equation (99) explicitly accounts for how the tax policy shifts the location of the entire counterfactual distribution below p^*. By contrast, the Kleven and Waseem (2013) polynomial fit of the earnings distribution effectively assumes that income taxes do not reduce labor supply other than to shift earnings around the notch. Second, as a result of this shift, the left-digit effects below p^* occur at different quantiles of L_0 versus L_1. For example, the left-digit effect at \$20,000 might be at the 26th percentile of L_1 but the 34th percentile of the downward-shifted L_0. Thus, to correctly predict the full counterfactual distribution F_0, we formally introduce notation for the latent distribution and separate the three steps described above.

Our standard errors on $\rho\tau_u$ reflects uncertainty in the left-digit effects Λ and in the polynomial fit. We follow Kleven and Waseem (2013) by using bootstrapped residuals to measure uncertainty in the polynomial fit, and sample Λ values to account for left-digit uncertainty.

One bootstrap iteration has the following steps. First, we assume Λ is normally distributed with zero covariance and make a draw $\tilde{\Lambda}$ using the standard error on Λ. Second, we compute the latent distribution $\tilde{l}_1$ implied by $\tilde{\Lambda}$ and estimate the $\widehat{\rho\tau_u}$ that solves the excess mass equation for this distribution, generating $\tilde{l}_0$. Third, we apply sampled residuals from the optimal regression in step two to $\tilde{l}_0$, forming $\hat{l}_0$. Fourth, we compute the $\widehat{\rho\tau_u}$ that solves the excess mass equation for $\hat{l}_0$.

Repeating these four steps 250 times generates a vector $\widehat{\boldsymbol{\rho\tau_u}}$. We take the standard error of $\rho\tau_u$ to be the standard deviation of $\widehat{\boldsymbol{\rho\tau_u}}$.

D.3 Bunching Results

This appendix subsection contains additional details on our results including robustness checks and monthly price histograms.

Figure A4 plots the monthly distribution of used EV transaction prices over \$15,001 to \$35,000. We present this figure to accompany the monthly estimates of $\widehat{\rho\tau_u}$ shown in Figure 4. Consistent with our empirical estimates, it is apparent visually that the excess mass (or "spike") in the \$24,000 bin varies substantially across months in 2023. The histograms exhibit a fair amount of noise, with monthly transaction counts averaging around 200 transactions per bin.

Our estimates of $\widehat{\rho\tau_u}$ in the main body use a fifth order polynomial, but our results are quite robust to alternative orders. Figure A5 shows the counterfactual fit for the 2024+ latent distribution estimated from equation (99) assuming different orders $K \in \{2, \ldots, 9\}$. The maroon bars are the calculated l_1 distribution (shifted by the optimal $\widehat{\rho\tau_u}$ for bins below the \$25,000 price cap), the grey bars are l_1 bins that are excluded, and the black line is the polynomial fit. The fit is consistent, with higher orders showing a moderately more "humped" look around \$25,000.

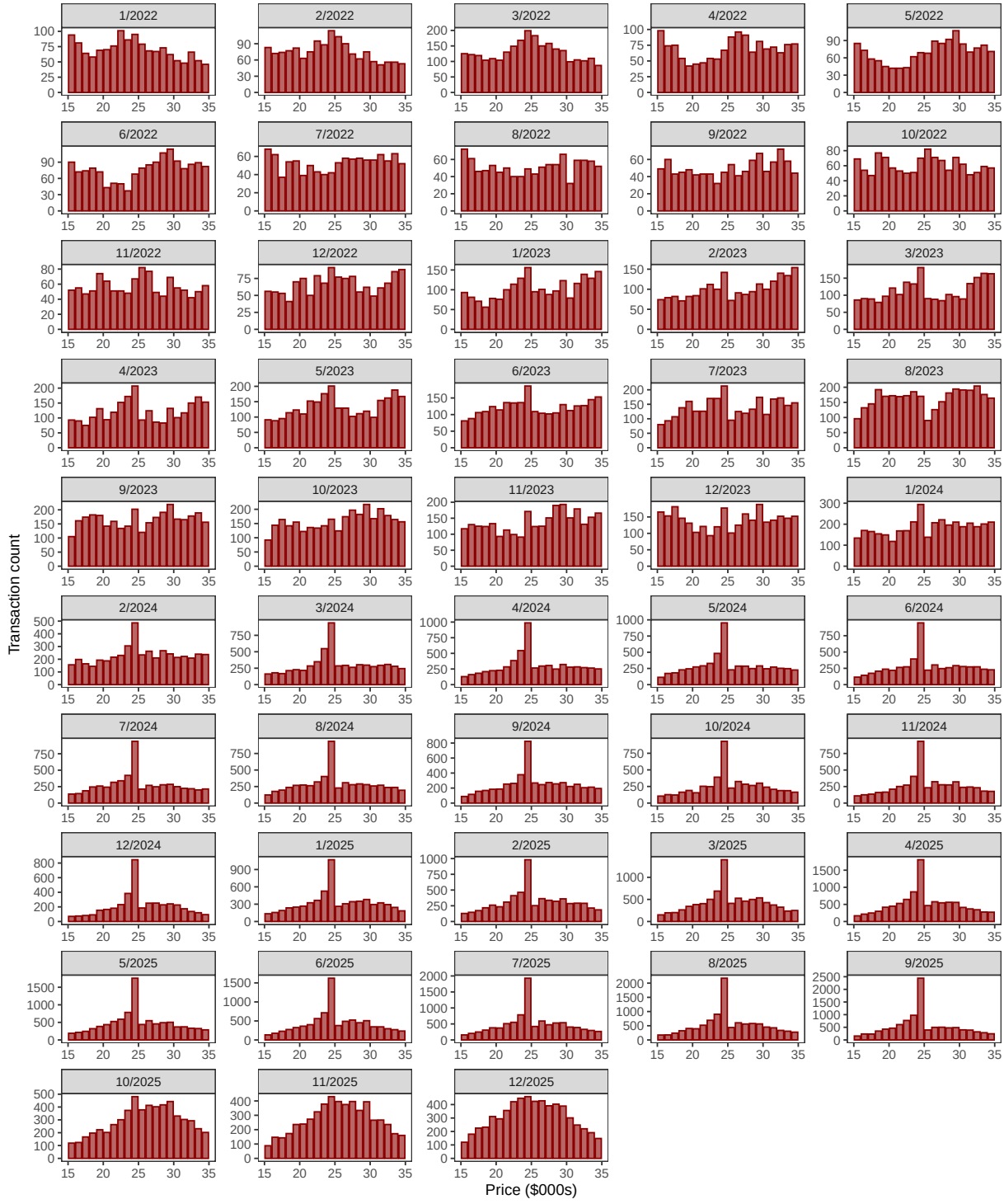
Figure A6 plots the $\widehat{\rho\tau_u}$ values for each polynomial order that solves the excess mass equation, where the whiskers represent 95 percent confidence intervals. We bootstrap standard errors, as explained in Appendix D.2. The maroon shows the 2024+ values while the blue plots values for 2023. Almost all estimates lie within the confidence interval of our primary fifth order polynomial. The fifth order estimate is also close to the median because it displays a moderate amount of curvature at \$25,000, as illustrated in Figure A5. The higher orders predict a higher counterfactual mass and thus lower $\widehat{\rho\tau_u}$.

We also include an estimate of a uniform fit, where we use the two bins immediately adjacent to each side of the excluded region. For example, we estimate the counterfactual mass over the lower region (from (\$23,000 - $\widehat{\rho\tau_u}$) to \$25,000) as the average mass over the l_1 bins at \$21,000 and \$22,000 (pre-shift). We perform the analogous procedure to predict the mass from \$25,001 to \$26,000. The resulting distribution is plotted in the first panel of Figure A5, where the black line illustrates our procedure given the $\widehat{\rho\tau_u}$ that solves the excess mass equation. We plot the $\widehat{\rho\tau_u}$ as polynomial order 1 in Figure A6, and it is consistent with the other polynomial fits.

In the body of the paper, we assume that excess mass can arise anywhere in a bunching region starting at $\underline{p}$ = \$23,001 and that downward bunching can occur for transactions that would be priced as high as $\overline{p}$ = \$26,000. Table A3 presents $\widehat{\rho\tau_u}$ estimates using our preferred fifth order polynomial with different assumptions for $\overline{p}$ and $\underline{p}$. The results are similar to our primary specification presented in the body.

Figure A7 shows that there is no visibly significant bunching in average APR by price bin. If there were bunching, this would not be a threat to internal validity. Bunching in APRs would have suggested that financing companies and possibly dealerships captured some of the incidence of the tax credit by increasing

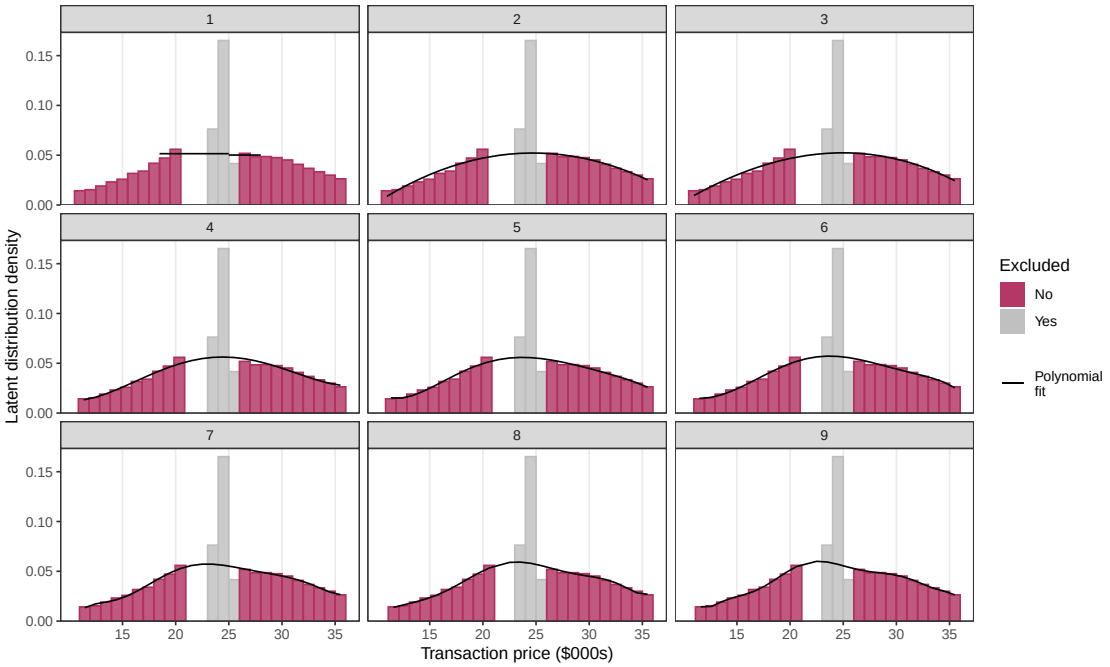
Figure A4: **Used EV Transaction Price Distributions by Month 2022-2025**



Notes: Each subplot shows the distribution of used EV transaction prices between $15,001 and $35,000 by month. Each bar represents a $1,000 bin.

other components of the vehicle's economic price.

Figure A5: **Fitted Counterfactual of 2024+ Distribution by Polynomial Order**



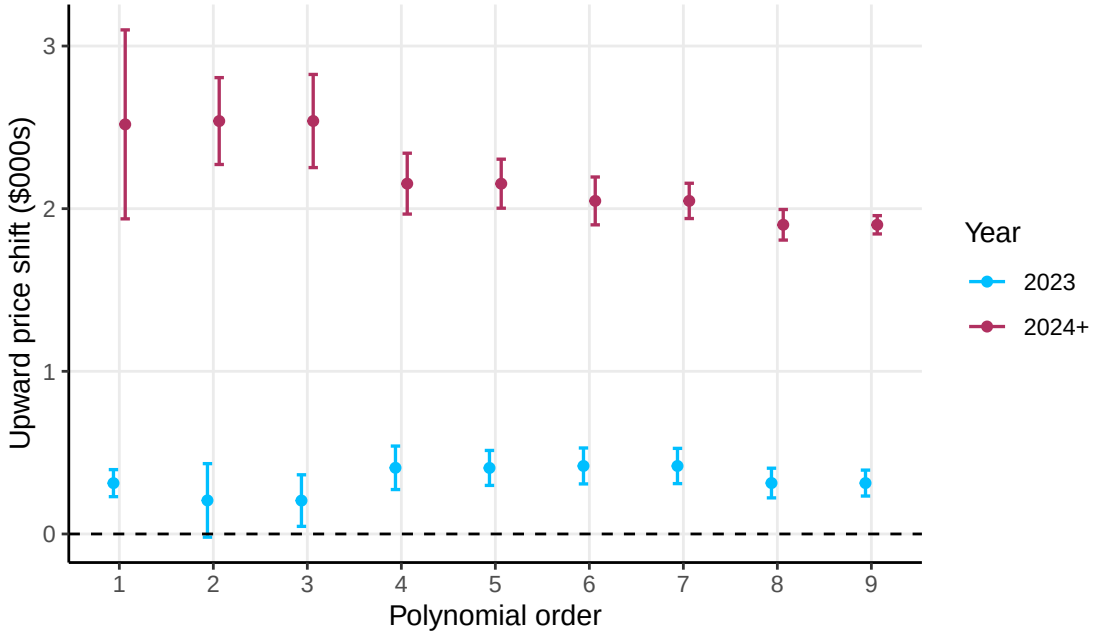
Notes: Each subplot shows the estimated counterfactual from equation (99) that solves the excess mass equation using polynomial orders 2–9. The uniform panel in the top left uses local uniformity on each side of the excluded region. Each bar represents a $1,000 bin.

Table A3: **Alternative Specifications**

	(1) 2022	(2) 2023	(3) 2024+
$\underline{p} = \$22,001$	209	557	2,481
	(92)	(60)	(61)
$\overline{p} = \$27,000$	170	324	2,080
	(69)	(61)	(83)

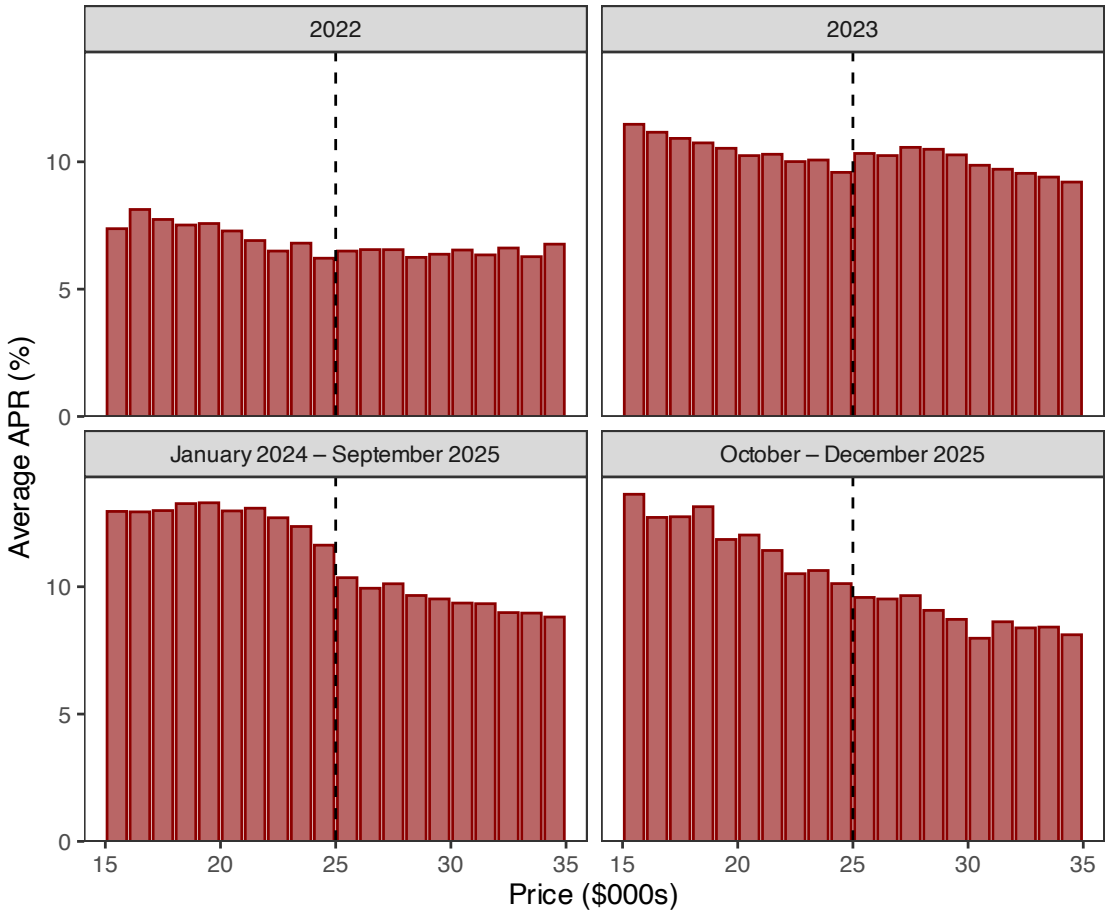
Notes: This table shows the resulting $\widehat{\rho\tau_u}$ that solves the excess mass equation for alternative specifications. We use a fifth order polynomial and the estimates are shown for the EV distribution.

Figure A6: $\rho\tau_{\mathbf{u}}$ **Estimates with 95 Percent Confidence Intervals**



Notes: We plot the estimated $\widehat{\rho\tau_u}$ by polynomial order that solves the excess mass equation. The whiskers represent 95 percent confidence intervals calculated via bootstrapping. For polynomial orders 2–9, we predict the counterfactual via a regression using equation (99). For polynomial order 1, we use local uniformity on each side of the excluded region, see text for details.

Figure A7: **Average APR by Price Bin**



Notes: This figure presents the average interest rate for financed used EVs that were at least two years old.

D.4 Changes in Dealership Transaction Shares

One threat to the smoothness assumption would be if more EVs expected to be sold at prices below $25,000 were sold through dealerships instead of private parties. This would increase the mass of transactions at prices below $25,000. This could happen in 2023, when the tax credits were first implemented, or in 2024, as dealership transfer began.

To test for shifting into the dealership market, we use the Experian data. The data include monthly transaction volumes for each model and model year for both dealership and private party transactions. We say "vehicle type" to refer to a model-by-model year combination.

The event study regression uses a triple-difference specification where the dependent variable is the ratio of dealership transactions to total (dealership plus private party) transactions. We compare dealership transaction share trends for low-priced versus high-priced EV vehicle types, compared to the differential trend for low-priced versus high-priced GV vehicle types. To group vehicle types into "low-priced" versus "high-priced," we merge the Cox dealership price data. We define the low-price group as vehicle types with greater than 50 percent of transactions below $21,000 during the sample period and the high-price group as vehicle types with greater than 50 percent of transactions between $35,000 and $50,000. We exclude all other vehicle types from the analysis.

For the 2023 event study, the regression sample spans July 2022 to July 2023, with the pre period from July to December 2022 and the post period from January to July 2023. For the 2024 event study, the sample spans July 2023 to March 2024, which is the final month of the Experian sample. We limit the sample to model years before 2022 to mitigate trends driven by newer models entering the used vehicle market. Since newer models are more likely to fall in the higher price category, control group quantities exhibit an upward trend even with this restriction.

Let j, y, b, and t, respectively, index model, model year, body type, and month of sample. Let A_t represent time. For the pre/post triple difference regression, A_t is a post period ("After") indicator. For the event study figures, A_t is a vector of month of sample indicators, excluding December (the last month of the pre period). Define EV_j as an EV indicator, and define G_{jy} as an indicator for the low-price group as defined above. Let R_{jyt} denote the dealership transaction share for vehicle model j and MY y. We include body type-by-month (γ_{bt}), model (γ_j), and model year (γ_y) fixed effects. The event study regression is

$$R_{jyt} = \beta_1 A_t EV_j G_{jy} + \beta_2 A_t EV_j + \beta_3 A_t G_{jy} + \beta_4 EV_j G_{jy} + \beta_5 G_{jy} + \gamma_{bt} + \gamma_j + \gamma_y + \epsilon_{jyt}. \tag{100}$$

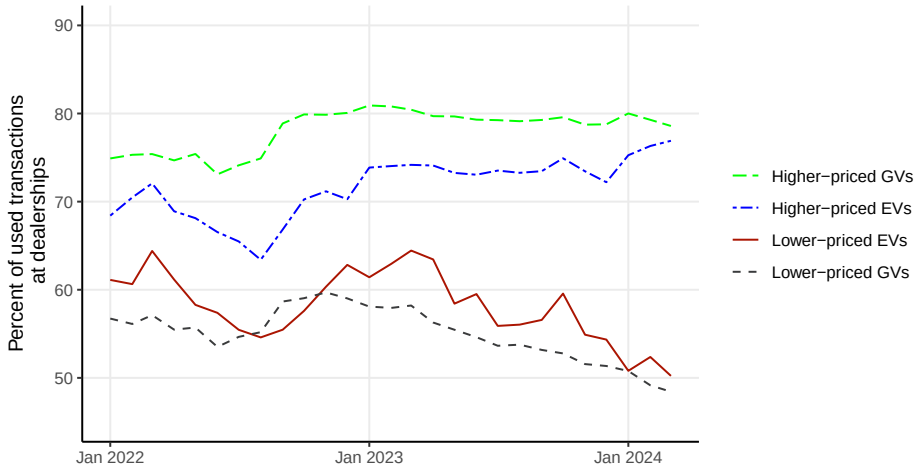
We weight observations by the monthly average number of transactions and cluster standard errors by vehicle model.

Figure A8 presents raw data trends that illustrate the triple-differences approach. A smaller share of lower-priced vehicle types are sold through dealerships over the course of 2023, but the trends are similar

for EVs and GVs. Figure A9 presents the β_1 coefficients in the dealership share event study specifications in 2023 and 2024. Both Panel (a) and Panel (b) suggest no statistically detectable change in dealership share of predicted-eligible EV transactions after the used EV tax credit policy changes. The formal diff-in-diff estimates in Table A4 correspondingly show no statistically significant changes.

Overall, these results suggest that individuals did not shift their selling behavior in the short run in response to the used EV tax credits. This is consistent with sellers having limited awareness of the policy or not expecting to receive additional payment from dealerships for potentially eligible vehicles.

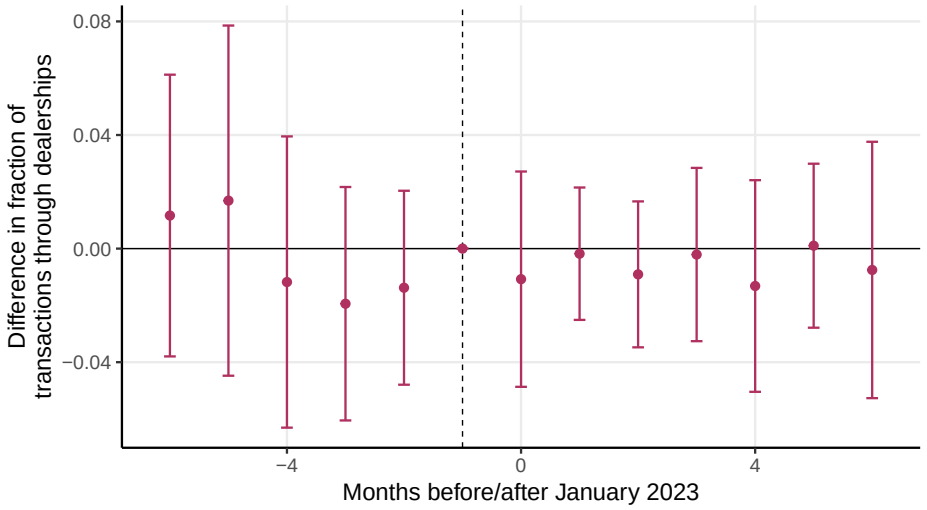
Figure A8: **Dealership Transaction Share by Powertrain and Price**



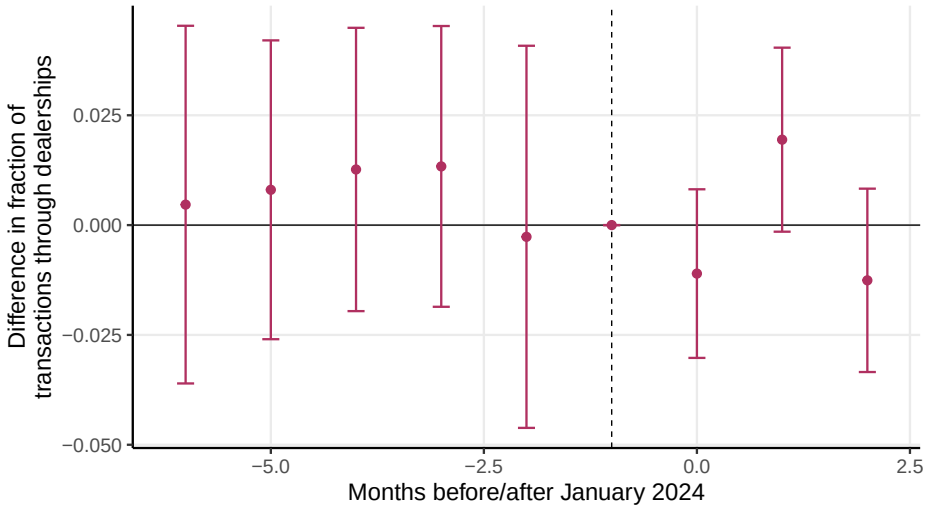
Notes: This figure shows the percent of used vehicle transactions sold through dealerships by treatment group from 2022 through early 2024. Treatment groups are based on fuel type and predicted price group.

Figure A9: **Dealership Share Triple-Differences Event Studies**

(a) 2023



(b) 2024



Notes: This figure presents β_1 coefficients from the event study estimator in equation (100), interpreted as the trend in dealership share for predicted-eligible EVs relative to predicted-ineligible EVs and GVs. Panels (a) and (b), respectively, present the event studies for the beginning of the tax credit in January 2023 and the availability of dealership transfer in January 2024. Whiskers indicate 95 percent confidence intervals.

Table A4: **Dealership Transaction Share Effects around January 2023 and January 2024**

	(1)	(2)
	2023	2024
	Dealership %	
EV × predicted price <$21k	-0.003	-0.007
× post-period	(0.013)	(0.010)
Fixed-effects		
Make × Time-to-treat	Yes	Yes
MY	Yes	Yes
Model	Yes	Yes
Observations	18,768	15,829

Notes: This table presents the results of the pre-post specification of equation (100). Columns (1) and (2), respectively, present estimates for 2023 and 2024. Our 2024 Experian data end after March of that year, so the sample size is smaller. An observation is a model-MY-month. Standard errors are clustered at the model level.

D.5 Share of Buyers that Are Credit-Eligible

In this section, we describe our approach to computing the average value of the used EV tax credit for price-eligible transactions at dealerships, accounting for buyer eligibility. As described in Section 2, the tax credit was non-refundable in 2023, but became refundable with dealership transfer starting January 1, 2024. Thus, we compute separate values for 2023 and 2024.

Our analysis uses two data sources. First, we use the 2023 NVES, a sample of new vehicle sales, where we observe the price, household income, marital status, and whether the buyer had children under the age of 18. As almost all new EVs are sold above $25,000, we use any purchase under $25,000 regardless of powertrain. In doing so, we make the assumption that buyers of used EVs costing under $25,000 have the same income distribution as buyers of new GVs costing under $25,000.

Second, we use IRS statistics of income (SOI) data for tax year 2022 (IRS 2025) to compute tax liability. For each filing status and adjusted gross income (AGI) bin, we observe the total number of tax returns, total tax liability, and the number of returns with tax liability greater than zero. In columns 5–8 of Table A5, we report the share of filers with strictly positive tax liability, for each AGI bin and filing status. In columns 9–12, we report the value of a non-refundable $4,000 tax credit conditional on having positive tax liability.

To join the IRS tax data to the NVES data and obtain appropriate bin by filing status weights, we assume reported household income in the NVES is the same as AGI. For filing status, we assign any non-married respondents as head of household if they report having children, and single filers otherwise. For married respondents, we divide them between filing jointly and separately based on the observed split in the IRS data for each AGI bin. The share of purchasers by income bin and filing status for our NVES subsample are in columns 1–4 of Table A5. Column 13 shows the average value of a non-refundable $4,000 subsidy for each income bin, averaging across filing statuses using weights from columns 1–4.

Our interest is the value of a $4,000 subsidy including the income-eligibility constraints for used EV tax credits under the IRA. The income limits are $75,000 for single and married filing separately, $112,500 for head of household, and $150,000 for married filing jointly purchasers. Combining the subsidy value results in columns 5–12, the weights in columns 1–4, and the income eligibility conditions, we compute the average value of $4,000 subsidy for each filing type and overall in the second to last row of Table A5. This is our estimate of the value of used EV tax credits on price-eligible transactions before January 1, 2024. Once the dealership transfer policy is enacted, we assume all eligible individuals will receive the full $4,000 benefit, so the only question is what fraction of individuals are income-eligible. We report this in the final row of Table A5 by filing status, with the overall share in column 13.

For tax year 2023, IRS (2025a) cites that 28,180 used EV credits were claimed, with an average amount of $3,392. By comparing this with the eligible transactions in the data, we can get an alternative estimate for the value of the used EV tax credits. To construct the data counterpart, we use two datasets. First, with our

Experian transactions data we calculate the number of used EV sales in 2023 that had model years 2021 and older that occurred at dealerships. Second, in the Cox data we find the fraction of used sales in 2023 costing under $25,000 and the average subsidy for eligible transactions capping the subsidy at 30 percent of price based on IRA rules. We join these at the level of make-model-model year to get an estimate of the used EV transactions eligible for tax credits as well as the subsidy amount. We find 66,016 potentially eligible transactions, which have an average available credit of $3,805.

We divide the dollar value of claimed credits from the IRS by our calculation of eligible transactions times subsidy amount, yielding 0.38. Put a different way, this implies the average value of a $4,000 subsidy was $1,520, which is the empirical analogue to our estimated 2023 value of $1,970 from Table A5.

D.6 Bunching Distribution Price Shift Table Methodology

This section describes how we compute the implied price shift for each part of the distribution f_1 after we identify $\widehat{\rho\tau_u}$. We presented these estimates in the main body as Panel (b) of Table 3. The basis of these calculations is our model of prices given in equation (96). We first describe our treatment of left-digit effects for individual observations before describing our computation of the table.

Let i denote a transaction with observed price p_{i1}. We model the latent price p_{i1}^L of observation i in a probabilistic manner where we assume any left-digit bias moves the price by $1,000. For example, if p_{i1} = $24,500, then

$$\mathbb{P}(p_{i1}^L = \$23{,}500) = \underline{\lambda}_5 l_1(23)/D \tag{101}$$

$$\mathbb{P}(p_{i1}^L = \$24{,}500) = l_1(24)/D \tag{102}$$

$$\mathbb{P}(p_{i1}^L = \$25{,}500) = \overline{\lambda}_5 l_1(25)/D, \tag{103}$$

where $\mathbb{P}$ denotes probability and $D = \overline{\lambda}_5 l_1(25) + l_1(24) + \underline{\lambda}_5 l_1(23)$. To convert from the latent distribution to the observed for a particular transaction, we again do this probabilistically using the left-digit bunching probabilities implied by Λ. Combined, these methodologies imply we can translate between p_{i1} to p_{i1}^L and p_{i0}^L back to p_{i0}.

We now describe our computation of the price shift in five distinct regions, each corresponding to a row of panel (b) of Table 3. First, suppose $p_{i1} \leq \$13{,}333$, then the IRA specified that the transaction was potentially eligible for a tax credit equal to 30 percent of the price. This implies that the latent distribution shifted upwards by $0.3 \cdot p_{i1}$ under complete pass-through. We scale this effect using our estimated pass-through rate $\widehat{\rho\tau_u}/4$ and calculate that $p_{i0}^L = p_{i1}^L - 0.3 p_{i1} \cdot \widehat{\rho\tau_u}/4$. We convert to p_{i1}^L probabilistically, as described above, then translate to p_{i0}^L as indicated, and finally compute p_{i0}. We then compute the expected value of the shift $p_{i1} - p_{i0}$.

Table A5: **Tax Liability Statistics**

	Share of purchases < $25k				Share with tax liability				Value of $4k tax subsidy | tax liability > 0				
Income	(1) Married filing jointly	(2) Married filing separately	(3) Head of household	(4) Single	(5) Married filing jointly	(6) Married filing separately	(7) Head of household	(8) Single	(9) Married filing jointly	(10) Married filing separately	(11) Head of household	(12) Single	(13) Average value within income bin
$1-20,000	0.4%	0.1%	1.3%	2.9%	0.1%	8.9%	0.0%	22.1%	$2,948	$186	$0	$327	$46
$20,000-25,000	0.4%	0.1%	0.2%	1.7%	0.3%	78.4%	2.5%	83.4%	$4,000	$921	$240	$868	$541
$25,000-30,000	0.8%	0.1%	0.6%	4.0%	17.9%	76.5%	8.0%	88.9%	$145	$1,441	$374	$1,418	$949
$30,000-40,000	1.7%	0.3%	1.3%	5.7%	47.4%	85.4%	14.4%	93.6%	$627	$2,139	$921	$2,227	$1,466
$40,000-50,000	2.4%	0.5%	1.4%	6.5%	56.5%	91.8%	51.8%	97.8%	$1,523	$3,220	$1,263	$3,356	$2,387
$50,000-75,000	8.9%	1.1%	2.1%	12.1%	76.9%	95.9%	83.5%	98.6%	$3,003	$4,000	$2,790	$4,000	$3,196
$75,000-100,000	8.7%	0.5%	1.8%	4.1%	93.0%	98.0%	96.4%	99.1%	$4,000	$4,000	$4,000	$4,000	$3,809
$100,000-200,000	17.0%	0.4%	1.5%	4.3%	98.5%	98.5%	98.8%	99.3%	$4,000	$4,000	$4,000	$4,000	$3,946
$200,000-500,000	4.0%	0.1%	0.1%	0.6%	99.8%	97.3%	99.3%	99.8%	$4,000	$4,000	$4,000	$4,000	$3,990
$500,000-1,000,000	0.1%	0.0%	0.0%	0.0%	99.9%	98.4%	99.5%	99.5%	$4,000	$4,000	$4,000	$4,000	$3,996
$1,000,000+	0.0%	0.0%	0.2%	0.0%	99.9%	99.3%	99.5%	99.7%	$4,000	$4,000	$4,000	$4,000	$3,984
Value of $4k tax subsidy under used EV tax credit eligibility									$2,006	$2,055	$1,301	$2,083	$1,966
Percentage of purchases that are income eligible for used EV tax credits									71.5%	68.5%	84.6%	78.5%	75.7%

Notes: This table uses the 2023 NVES and 2021 IRS statistics of income data to calculate the value of a non-refundable $4,000 tax credit to price-eligible used EV buyers under IRA income-eligibility rules. Columns 1–4 show the weighted share of transactions in the NVES for vehicles costing under $25,000 by income and filing status. Columns 5–8 show the share of filers with tax liability. Columns 9–12 show the value of a non-refundable $4,000 subsidy among filers with tax liability. Column 13 computes the average credit value within each income bin. The second to last row utilizes the IRA used EV tax credit income limits of $75k, $112.5k, and $150k for single and married filing separately, head of household, and married filing jointly filers, respectively, to compute the average credit value accounting for zero tax liability filers. The final row uses only income eligibility and the shares in columns 1–4.

Second, consider \$13,333 $\leq p_{i1} \leq$ \$23,000. In this region, the vehicle is potentially eligible for a credit of \$4,000, so, similarly to above, we assume $p_{i0}^L = p_{i1}^L - \widehat{\rho\tau_u}$. We then proceed as in region one above.

Third, suppose $p_{i1} >$ \$26,000, then by the assumptions of our model, $p_{i0} = p_{i1}$.

Fourth, to calculate the downward bunching we compute the probability d that a transaction bunches downwards, following equation (96). We calculate

$$d := \frac{\Big(F_0(26) - F_0(25)\Big) - \Big((F_1(26) - F_1(25)\Big)}{F_0(26) - F_0(25)}, \tag{104}$$

where the numerator is the estimated missing mass in the upper bin, meaning d can be interpreted as the share of the counterfactual bin that bunched downwards. We make the assumption that these transactions bunched downwards either by \$1,000, with probability d_1, or \$2,000, with probability d_2. We assume $d_1/d_2 = F_1(24)/F_1(23)$ and enforce $d_1 + d_2 = d$. Using this, we define the average downward bunching force for prices \$25,000 $\leq p_{i0} \leq$ \$26,000 as $-d_1 - 2d_2$.

For the fifth region, we want a measure of the upwards shift to the observed \$23,000 to \$25,000 region. To disentangle the upward shift and downward bunching, we utilize the excess mass equation that $L_1(26) - L_1(23) = L_0(26) - L_0(23 - \widehat{\rho\tau_u})$. Using our assumption on the left-digit effects and adding/subtracting $F_1(25)$ and $F_0(25)$, we can reformulate this as

$$F_1(26) - F_1(25) + F_1(25) - F_1(23) = F_0(26) - F_0(25) + F_0(25) - L_0(23 - \widehat{\rho\tau_u}). \tag{105}$$

By definition of d, note that $(1 - d) \cdot [F_0(26) - F_0(25)] = [F_1(26) - F_1(25)]$, then we simplify further as

$$F_1(25) - F_1(23) - d[F_0(26) - F_0(25)] = F_0(25) - L_0(23 - \widehat{\rho\tau_u}). \tag{106}$$

This equation gives a transaction mass equivalence on the excluded interval of \$23k to \$25k after subtracting our downward mass calculation. Therefore, the difference in the average price on the left-hand side versus the right-hand side is our measure of the upward price shift. To calculate the left-hand side, we compute the average price in the 23k and 24k bins and then create a weighted average using weights $f_1(23) - d_2 f_0(25)$ and $f_1(24) - d_1 f_0(25)$, respectively.

To compute the average price on the right-hand side of equation (106), we need to use prices from the F_0 distribution. Therefore, we reformulate as

$$\Big[F_0(25) - F_0(23 - \widehat{\rho\tau_u})\Big] + \Big[F_0(23 - \widehat{\rho\tau_u}) - L_0(23 - \widehat{\rho\tau_u})\Big] \tag{107}$$

and compute average prices for each bracketed group by assuming bin uniformity and the f_0 price for any transactions falling within $F_0(23 - \widehat{\rho\tau_u}) - L_0(23 - \widehat{\rho\tau_u})$. To get a final price we use a transaction-weighted average.

E Structural Model Appendix

E.1 Scrappage Model and Parameterization

E.1.1 Scrappage Model

We assume that the distribution of wear-and-tear draws ($\zeta \sim G$) is such that $g_{ja}(p_{jat})$ is isoelastic with respect to price.

$$g_{ja}(p_{jat}) = \min\left\{\exp(\eta^a a)\cdot\left(\frac{p_{jat}-v_j^s}{\psi_j}\right)^{\eta^p},\ 1\right\}. \tag{108}$$

The scrap rate can never exceed $g_{ja} = 1$. If the price drops below $p_{jat} < v_j^s + \psi_j \exp(\eta^a a)^{-1/\eta^p}$, then vehicles are never worth reconditioning, and $g_{ja} = 1$.

Eligible VINs have higher resale prices due to the eligibility premium p_{jat}^e. Thus, eligible VINs have an analogous scrap rate equation, except with $p_{jat} + p_{jat}^e$.

E.1.2 Scrappage Model Estimation

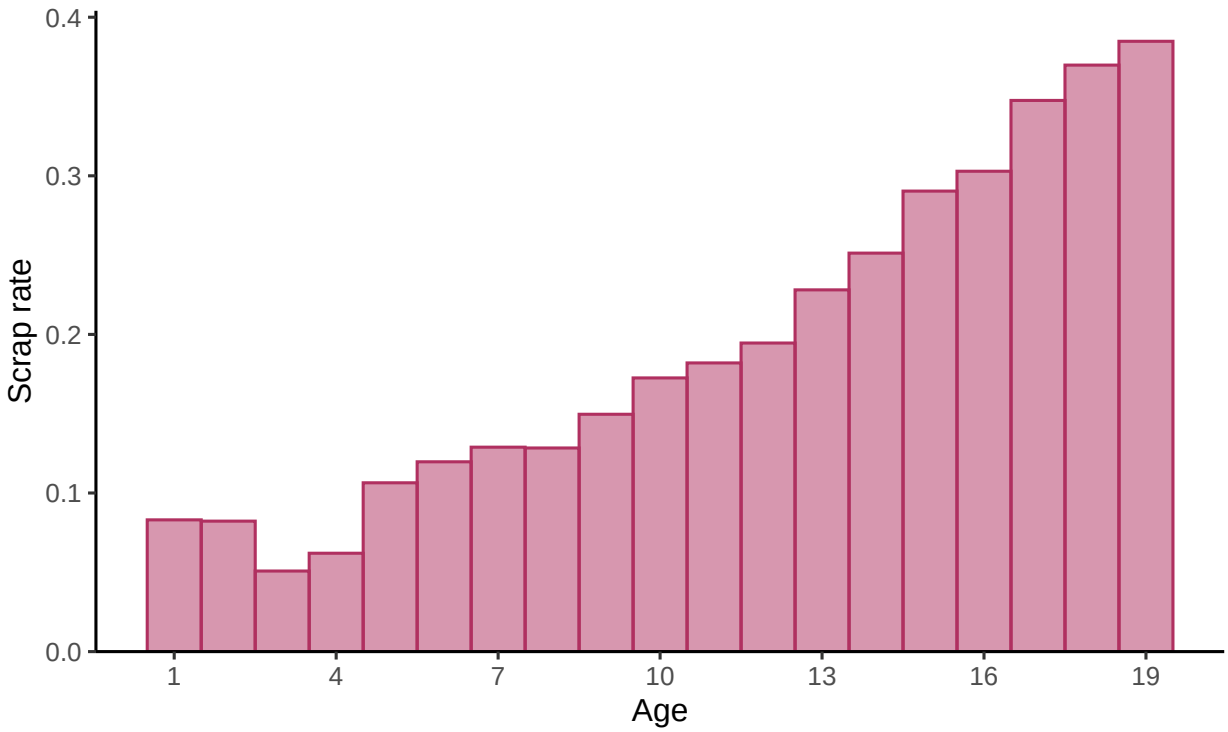
The necessary parameters for the scrappage model above are η^a (the age effect on scrappage), η^p (the price elasticity of scrappage), ψ_j (the model-specific scrap rate shifter), and r_j^s (the scrap value). As described in Section 6.1, we calibrate the scrap elasticity to -0.7 and assume scrap values $v_j^s = \$1000$ for EVs and $v_j^s = \$500$ for GVs.

We empirically estimate η^a and the ψ_j for each car type. To do this, we define q_{ja} as the number of transactions observed in the October 2022-September 2023 Experian data, and we compute scrap quantity q_{ja}^s as the decrease in the stock of registrations from the beginning to the end of that period, winsorized from below at 1 to ensure that it is positive. We then construct the observed scrap rate $g_{ja} = \frac{q_{ja}^s}{q_{ja}+q_{ja}^s}$. (Consistent with the model, this is the scrap rate for vehicles arriving on the market at the end of their holding periods, not the scrap rate as a percentage of the total stock.) We then log equation (108), substitute $\gamma_j = 0.7\ln(\psi_j)$, and re-arrange, giving the following estimating equation:

$$\ln(g_{ja}) + 0.7\ln(p_{ja} - v_j^s) = \eta^a a + \gamma_j + \epsilon_{ja}. \tag{109}$$

Figure A10 presents the average scrap rate by age. Table A6 presents the estimates of equation (109). We estimate $\eta^a \approx 0.08$, meaning that scrap rates increase by about 8 percent with each year of a vehicle's age. After estimating equation (109), we winsorize the car type fixed effects ψ_j at the 10th and 90th percentile for use in the structural model.

Figure A10: **Average Scrap Rate by Age**



Notes: This figure presents the average scrap rate by age, weighting observations by 2023 transactions.

Table A6: **Scrap Parameter Estimation**

	(1)
	$\ln(g_{ja}) + 0.7\ln(p_{ja} - v_j^s)$
Age	0.0831
	(0.0056)
Constant	-0.5304
	(2.860)
Observations	1,509

Notes: This table presents estimates of equation (109). An observation is a car type by age. New vehicles are excluded, because they are not scrapped. Observations are weighted by 2023 transactions.

E.2 Demand Model

E.2.1 Demand Estimation Overview

As described in Section 6.2, we follow Berry and Pakes (2007) in implementing the pure characteristics model via nested logit, setting $\mu_\epsilon = 5$.[17] Define $V_{ijyt} := U_{ijyt}/H_i - \varepsilon_{ijy}$ as the consumer's annualized utility net of the logit shock, and further define $L_{ijt} := \frac{1}{\mu_\epsilon} \ln(\sum_k \exp(V_{ijkt} \cdot \mu_\epsilon))$ as the normalized log-sum over ages. The choice probability is

$$Pr_{ijyt} = \underbrace{\frac{\exp(V_{ijyt} \cdot \mu_\epsilon)}{\sum_k \exp(V_{ijkt} \cdot \mu_\epsilon)}}_{\text{age choice probability, within model}} \times \underbrace{\frac{\exp(L_{ijt})}{\sum_j \exp(L_{ijt})}}_{\text{model choice probability}} . \tag{110}$$

Define $\boldsymbol{p}_t$ and $\boldsymbol{p}_t^e$ as the vectors of prices and eligibility premiums for all car types and ages at time t. Aggregate demand is the sum over consumers of their choice probabilities: $D_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}_t^e) = \sum_i Pr_{ijyt}$. Demand among consumers with holding period h is $D_{jyt}^h(\boldsymbol{p}_t, \boldsymbol{p}_t^e) := \sum_i \mathbb{1}(H_i = h) \cdot Pr_{ijyt}$. Total demand among eligible consumers is $D_{jyt}^e(\boldsymbol{p}_t, \boldsymbol{p}_t^e) := \sum_i e_i \cdot Pr_{ijyt}$.

The estimation requires several types of exogenous parameters.

- **Market size**. We set the market size N equal to the observed number of new and used vehicle transactions in 2023: about 42.1 million.
- **Resale price expectations**. The isoelastic scrappage assumption delivers a closed form for expected resale values $\tilde{v}_{jat}(\tilde{p}_{jat})$ as a function of market prices. While the counterfactual simulations assume that future price expectations $\tilde{p}_{jy,t+H_i}$ are correct in equilibrium, the initial demand estimation assumes that expectations are consistent with observed depreciation rates. Appendix E.2.2 provides details.
- **Holding time distribution**. We back out the distribution of holding times H_i from the 2009 NHTS, where respondents report the month and year that they originally bought their vehicles. The median holding time is 4 years. We assume that this distribution is stationary, i.e. that consumers in the market have the same distribution of H_i in each year. Appendix E.2.3 provides details.
- **Income distribution**. We approximate the income distribution by fitting a lognormal distribution to recent new and used vehicle buyers in the 2022 NHTS, winsorizing the fit at the 95th percentile. About 95 percent of consumers have household income below $300,000 per year and are thus modeled as eligible for the new EV tax credits in the demand estimation. About 77 percent of consumers have household income below $150,000 per year and are thus eligible for the used EV tax credits.

[17] Appendix Table A12 presents results with alternative values.

- **Tax credit amounts**. For estimation, we use new and used EV tax credit amounts τ_{jyt} consistent with IRA rules as of January 2023. Specifically, the new EV tax credit amounts account for final assembly and battery content requirements as well as MSRP limits,[18] and the used EV tax credit amounts are the minimum of $4,000 or 30 percent of price, for car-type year combinations jy with prices below $25,000.

With those exogenous parameters in hand, we then estimate the distributions of preference parameters α_i^p and $\boldsymbol{\alpha}_i^X$ and the vector of vertical qualities $\boldsymbol{\delta}$ using an approach analogous to Berry, Levinsohn, and Pakes (2004). We impose the following parameterizations. We let the marginal utility of money vary directly with income: $\alpha_i^p = \alpha_0/\ln(inc_i)$. We want to allow consumers to have flexible heterogeneous preferences over three key margins of substitution: EVs versus GVs, new versus used vehicles, and vehicle age. Thus, we define $\boldsymbol{X}_{j,a+h} := \{EV_j, \mathbb{1}(a = 0), (a + h)\}$. We let the three preference parameters $\boldsymbol{\alpha}_i^X$ differ for consumers with household income over $150,000 and also according to a random coefficient vector $\boldsymbol{\nu}_i$:

$$\boldsymbol{\alpha}_i^X = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_{inc}\mathbb{1}(inc_i > \$150k) + \boldsymbol{\sigma}\boldsymbol{\nu}_i. \tag{111}$$

We assume that the three random coefficients are independent, except for the correlation between EV and new vehicle tastes described in Appendix E.2.4. The EV taste shock ν_i^{EV} is distributed standard normal, while the new vehicle and vehicle age shocks ν_i^{new} and ν_i^{age} are distributed standard lognormal to ensure that they are positive. We constrain $\alpha_0^{EV} = 0$, so any additional vertical quality difference for EVs is simply subsumed into their δ_{jy}.

We let vertical quality differ by model and an unobserved shifter ξ_{jy}: $\delta_{jy} = \gamma_j + \xi_{jy}$. Since $\boldsymbol{X}_{j,a+h}$ captures preferences for new vehicles and younger used vehicles, we assume that δ_{jy} does not vary by age.

Our estimation routine broadly follows Berry, Levinsohn, and Pakes (2004). Define $\boldsymbol{\Theta} := \{\alpha_0^p, \alpha_0^{new}, \alpha_0^{age}, \alpha_{inc}^{EV}, \alpha_{inc}^{new}, \alpha_{inc}^{age}, \sigma^{EV}, \sigma^{new}, \sigma^{age}, \rho_{EV,new}\}$ as a vector of ten parameters, and define $\boldsymbol{M}(\Theta)$ as a vector of ten moment conditions described below. We iterate over three steps until convergence:

1. use the Berry (1994) contraction mapping to get $\boldsymbol{\delta}|\boldsymbol{\Theta}$;
2. regress $\delta_{jy} = \gamma_j + \xi_{jy}$ to get $\boldsymbol{\xi}$;
3. minimize $\boldsymbol{M}(\Theta)\boldsymbol{M}(\Theta)'$ to get $\boldsymbol{\Theta}|(\boldsymbol{\delta}, \boldsymbol{\xi})$.

We have one moment condition for each of the ten parameters. The identification is intuitive; we present Andrews, Gentzkow, and Shapiro (2017) sensitivity matrices in Appendix Tables A10 and A11. We use four types of moment conditions.

[18] We use the Actual MSRP variable in our Cox dataset minus a fixed $2,000 as a heuristic for transportation costs which are excluded from the MSRP requirement per IRS rules. We calculate the share of transactions that are under $55,000 for cars and $80,000 for SUVS and trucks and assume the credit to be the statutory maximum times this share.

1. **Average firm-level price elasticity**. One moment matches average firm-level price elasticity for the five firms (Ford, GM, Toyota, Volkswagen, and Hyundai) reported in Grieco, Murry, and Yurukoglu (2024), which is -4.69. We rely on the Grieco, Murry, and Yurukoglu (2024) elasticity estimate because their price instrument (based on exchange rate variation) is particularly credible. The price response parameter α_0^p is particularly sensitive to this moment.

2. **Independent unobservables**. Two moments assume zero covariance between unobserved quality ξ and two product characteristics $\boldsymbol{X}$: the new vehicle indicator and the age of used vehicles. The new vehicle and age intercepts α_0^{new} and α_0^a are particularly sensitive to these moments.

3. **High-income moments**. Three moments match the averages of the three vehicle characteristics $\boldsymbol{X}$ for higher-income consumers, using NVES and 2022 NHTS microdata. The income shifters $\boldsymbol{\alpha}_{inc}$ are particularly sensitive to these moments.

4. **Within-consumer moments**. Four final moments match the covariance of vehicle characteristics across different choices made by the same household. Using NVES data, we construct the share of new EV buyers whose second choice was an EV, separately for buyers whose second choice was a new vehicle and buyers whose second choice was a used vehicle, as well as the share of new vehicle buyers whose second choice was a new vehicle. Using two-vehicle households in the 2009 NHTS (which unlike the 2022 survey, has purchase date for all vehicles), we construct the correlation between the two vehicles' ages at purchase, conditional on the first vehicle being bought used. The random coefficient dispersions $\boldsymbol{\sigma}$ and the EV–new taste correlation $\rho^{EV,new}$ are particularly sensitive to these moments.

Appendix E.2.4 presents formal details on the estimator and moment conditions. Appendix E.2.5 presents the empirical moments and parameter estimates.

E.2.2 Expected Resale Values

Given isoelastic scrappage as characterized in equation (108), a vehicle's expected resale value in all ages $a \leq 19$ is

$$\tilde{v}_{jat}(\tilde{p}_{jat}) = g_{ja}(\tilde{p}_{jat}) \cdot v_j^s + (1 - g_{ja}(\tilde{p}_{jat})) \cdot \tilde{p}_{jat} - \psi_j \int_{\exp(\eta_a a)^{-\frac{1}{\eta_p}}}^{\frac{\tilde{p}_{jat} - v_j^s}{\psi_j}} x \, dG(x). \tag{112}$$

As in Section 3, tildes on p and v indicate that these are consumers' expectations of future values. For vehicles aged $a \geq 20$, which we assume are always scrapped at the end of their holding periods, the scrap rate is $g_{ja} = 1$, and the expected resale value is just $\tilde{v}_{jat} = v_j^s$.

For our counterfactual simulations, we assume that consumers have rational expectations, i.e. that their expectations of future used vehicle market prices are correct in equilibrium. For the initial demand parameter estimation, however, we assume that consumers' expectations of future used vehicle market prices $\tilde{p}_{jat}$ are consistent with a regression fit in the 2023 cross section, weighting by transaction count:

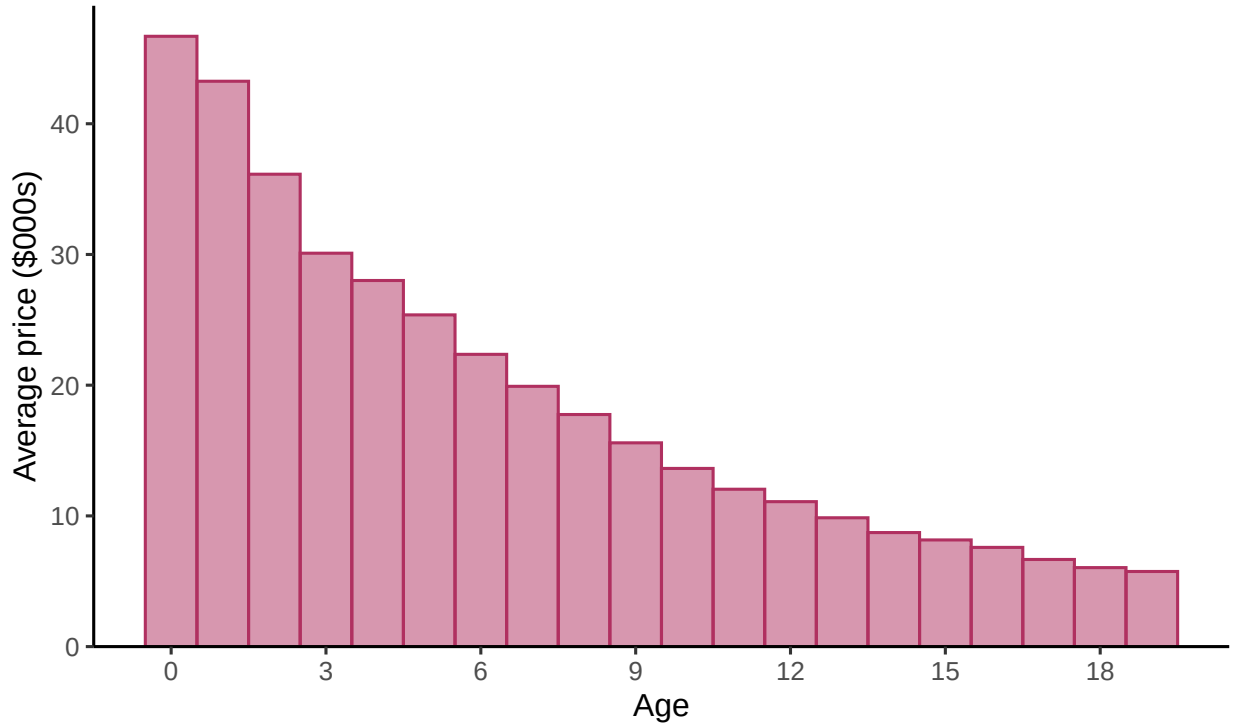
$$\ln(p_{jy,2023}) = \beta^n \mathbb{1}(y = 2023) + \beta^a a + \gamma_j + \epsilon_{jy}. \tag{113}$$

Figure A11 presents the average price by age. Table A7 presents the estimates of equation (113). We estimate $\beta^a \approx -0.11$, meaning that vehicles depreciate by about 11 percent per year. For the demand estimation, we construct consumers' price expectations as the (observed) market price $p_{jy,2023}$ adjusted for predicted depreciation over the consumer's holding period H_i:

$$\ln(\tilde{p}_{jy,2023+H_i}) = \ln(p_{jy,2023}) - \hat{\beta}^n \mathbb{1}\{y = 2023\} + \hat{\beta}^a H_i, \tag{114}$$

for all t. We then construct resale value expectations by evaluating equation (112) at $\tilde{p}_{jy,2023+H_i}$.

Figure A11: **Average Price by Age**



Notes: This figure presents the average vehicle price by age, weighting observations by 2023 transactions.

Table A7: **Price Expectation Fit for Demand Estimation**

	(1)
	$\ln(p_{ja})$
Age	-0.1085
	(0.0007)
New	0.0202
	(0.0088)
Fixed effects	
Model	Yes
Observations	1,616

Notes: This table presents estimates of equation (113). An observation is a car type by age.

E.2.3 Holding Time Distribution

We use survey data from the 2009 NHTS to obtain a nationally representative sample of the distribution of time since purchase (in months) for vehicle owners in the U.S. The survey gives the current length of time each vehicle has been held. However, the relevant measure for our model is the distribution of holding times for consumers in the market each year.

We compute the distribution of holding time for vehicle owners, denoted $\Gamma^O(h)$, by assuming that owners with holding time h have uniformly distributed time since purchase between 1 and h at the time of the survey. Concretely, this says that for consumers with holding time h, a mass of $\Gamma^O(h)/h$ of these owners have holding times $1, \ldots, h$. We cap holding time at 30 years, winsorizing observations greater than 30 years. We also take a three-year moving average to mildly smooth the NHTS data. Let $\Gamma^{NHTS}(h)$ denote the distribution of time since purchase in the 2009 NHTS, then by our assumption $\forall h \in \{1, \ldots, 30\}$,

$$\Gamma^{NHTS}(h) = \sum_{k=h}^{30} \frac{\Gamma^O(k)}{k}. \tag{115}$$

Due to our holding time cap at 30 years, the system of equations given in equation (115) is equivalent to recursively solving

$$\Gamma^O(h) = h \cdot (\Gamma^{NHTS}(h) - \Gamma^{NHTS}(h+1)). \tag{116}$$

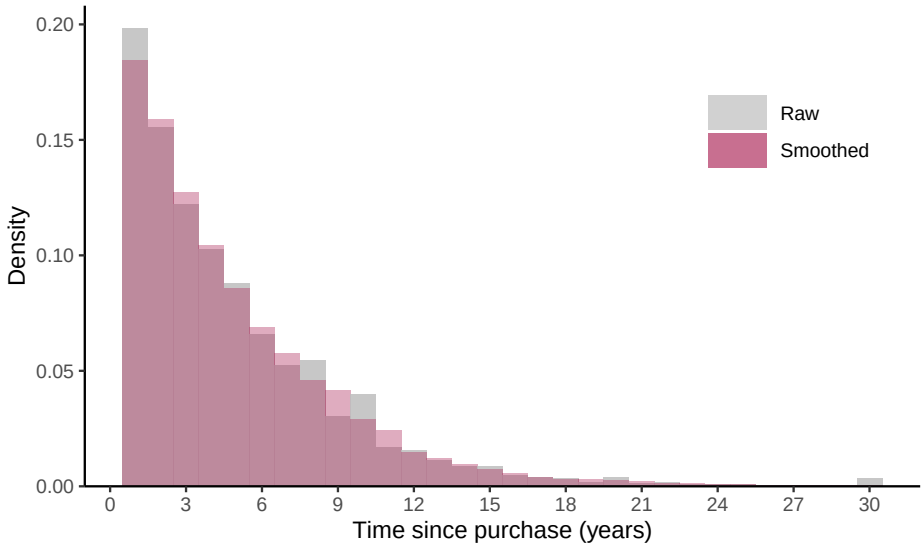
Therefore, if $\Gamma^{NHTS}(h+1) > \Gamma^{NHTS}(h)$, then $\Gamma^O(h) < 0$. Thus, we force weak monotonicity on Γ^{NHTS}. The raw distribution of Γ^{NHTS} and the smoothed version are shown in panel (a) of Figure A12.

The computed distribution of Γ^O, shown as grey bars in Panel (b) of Figure A12, is unrealistically bumpy. We perform smoothing parametrically by fitting a skew normal distribution, shown in maroon in Panel (b) of Figure A12. We winsorize at 20 to compute the final $\Gamma^O(h)$ over $H = \{1, \ldots, 20\}$. The median holding time among vehicle owners is 8 years.

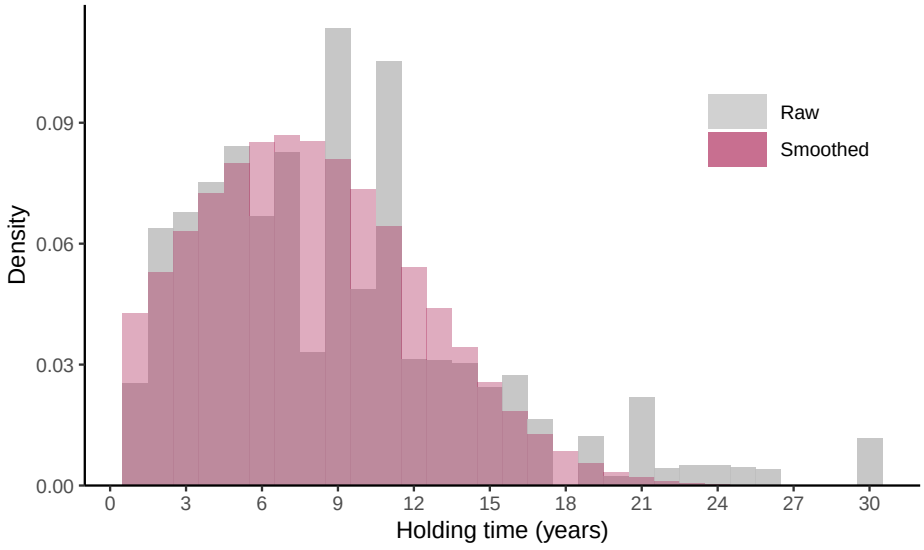
To convert from the holding time distribution of vehicle owners, Γ^O, to the holding time distribution of vehicle buyers, Γ, we need to adjust for how often each vehicle owner will enter the vehicle market. For example, an owner with holding time one will enter 20 times more often than an owner of holding time 20. Therefore, we set $\Gamma(h) = \Gamma^O(h)/h, \forall h$ and normalize to a valid distribution. This creates a stationary distribution Γ throughout our simulation.

Figure A12: **Holding Time Distributions in 2009 NHTS Cross-Section**

(a) **Distribution of Time Since Purchase**



(b) **Distribution of Holding Times**



Notes: This figure uses data from the 2009 National Household Travel Survey. Panel (a) presents the distribution of time since purchase. Using equation (115), we then calculate the implied distribution of holding times, shown in Panel (b). Each panel shows the distribution before smoothing, in grey, and after smoothing, in maroon.

E.2.4 Estimator and Moment Conditions

Our estimator of the preference parameter vector $\boldsymbol{\Theta}$ is

$$\hat{\boldsymbol{\Theta}} = \arg\min \boldsymbol{M}(\Theta)\boldsymbol{M}(\Theta)', \quad s.t.\ q_{jy} = \sum_i Pr_{ijy}(\boldsymbol{\Theta}). \tag{117}$$

The model is just-identified, so parameter estimates would not depend on the weighting matrix.

We now describe the four types of moment conditions. Since the demand estimation uses data for only $t = 2023$, we drop any t subscripts to be concise.

Average firm-level price elasticity. Our first moment condition matches the simulated average price elasticity of five major firms to the Grieco, Murry, and Yurukoglu (2024) estimate of -4.69. Define $\mathcal{F} := \{\text{Ford, GM, Toyota, Volkswagen, Hyundai}\}$ as the set of five firms, define $D^f_{2023} := \sum_{j\in\mathcal{J}_f, y=2023} D_{jyy}(\boldsymbol{p}_t, \boldsymbol{p}^e_t)$ as total demand for firm f's new vehicles in 2023, and define p^f_{2023} as a uniform proportional price shifter for firm f's model year 2023 vehicles. The moment condition is

$$M^p(\boldsymbol{\Theta}) = \frac{1}{5}\sum_{f\in\mathcal{F}} \frac{dD^f_{2023}}{dp^f_{2023}} \frac{p^f_{2023}}{D^f_{2023}} - (-4.69). \tag{118}$$

Independent unobservables. Our second type of moment condition leverages an assumed independence between product characteristics $\boldsymbol{X}$ and unobserved quality $\boldsymbol{\xi}$. We let x_{jy} represent individual vehicle characteristics. There are two of these moments, for the new vehicle indicator and vehicle age: $x \in \{\mathbb{1}(a = 0), (a + h)\}$. For each variable, these moment conditions set to zero the covariance between that variable and ξ:

$$M^X(\boldsymbol{\Theta}) = \sum_j \sum_y x_{ja}\xi_{ja}. \tag{119}$$

High-income moments. Our third type of moment condition matches average vehicle characteristics for high-income consumers. There are three of these moments, for each of the three vehicle characteristics: $x \in \{EV_j, \mathbb{1}(a = 0), (a + h)\}$. Define μ_{inc} as the share of consumers with household income below \$150,000 and $\hat{x}^{inc}$ as the empirically estimated average characteristic for vehicles bought by high-income consumers. The moment conditions are

$$M^{inc}(\boldsymbol{\Theta}) = \frac{1}{N\cdot(1-\mu_{inc})} \sum_{i|inc_i>\$150k} \sum_j \sum_y Pr_{ijy}x_{jy} - \hat{x}^{inc}. \tag{120}$$

Within-consumer moments. Our fourth type of moment condition uses vehicle characteristics across different choices made by the same consumer: first-choice and second choice vehicles from the NVES, or two vehicles owned by the same household from the NHTS. There are again four of these moments, one

for each of the three vehicle characteristics x and one for the correlation in preferences for EVs and new vehicles.

For the EV characteristic, $x_j = EV_j$, we use two moments, which also identify the correlation between EV and new vehicle preferences. Among consumers who bought a new EV, we match the share whose second choice is an EV, separately for those whose second choice is a new vehicle and those whose second choice is a used vehicle. This is consistent the construction of the NVES survey, which only surveys consumers with a first choice of a new vehicle. Define $Pr^{(2)}_{ij'y'|jy}$ as the simulated second choice probability: the probability that consumer i chooses car type j' of model year y' as a second choice conditional on choosing car type j of model year y as a first choice. Let $\mathcal{Y}^{new}$ and $\mathcal{Y}^{used}$ denote the new and used model years, and for $\ell \in \{new, used\}$ define

$$S^{EV,\ell}(\boldsymbol{\Theta}) = \frac{\sum_i \sum_{j \mid EV_j=1} Pr_{ij,2023} \sum_{y' \in \mathcal{Y}^\ell} \sum_{(j',y') \neq (j,2023) \mid EV_{j'}=1} Pr^{(2)}_{ij'y'|j,2023}}{\sum_i \sum_{j \mid EV_j=1} Pr_{ij,2023} \sum_{y' \in \mathcal{Y}^\ell} \sum_{(j',y') \neq (j,2023)} Pr^{(2)}_{ij'y'|j,2023}} \tag{121}$$

as the simulated EV share of new EV buyers' second choices of age group ℓ. With $\hat{x}^{(2),new}$ the observed analogue, the moment condition is $M^{12,EV}(\boldsymbol{\Theta}) = S^{EV,new}(\boldsymbol{\Theta}) - \hat{x}^{(2),new}$.

For the new vehicle characteristic, $x = \mathbb{1}(a = 0)$, we match the share of new vehicle buyers (of any powertrain) whose second choice is also a new vehicle. Using the second choice probabilities defined above, the simulated share is

$$S^{new}(\boldsymbol{\Theta}) = \frac{\sum_i \sum_j Pr_{ij,2023} \sum_{y' \in \mathcal{Y}^{new}} \sum_{(j',y') \neq (j,2023)} Pr^{(2)}_{ij'y'|j,2023}}{\sum_i \sum_j Pr_{ij,2023}}, \tag{122}$$

and with $\hat{x}^{(2)}_{new}$ the share observed in the NVES, the moment condition is $M^{12,new}(\boldsymbol{\Theta}) = S^{new}(\boldsymbol{\Theta}) - \hat{x}^{(2)}_{new}$.

For the age characteristic, $x = a + h$, we match the correlation coefficient between two vehicles owned by the same household. Since the NVES samples only new vehicle buyers, for this empirical moment we use NHTS data on households with two vehicles instead of the NVES second-choice survey question. This means that we are modeling two separate choice occasions, not the second choice from the same choice occasion. In constructing the observed and simulated moments, we condition on the first vehicle being bought used. This helps to separately identify preferences for age σ^{age} from preferences for new cars σ^{new}. Define $\hat{\rho}^x$ as the observed correlation in age between two vehicles owned by the same household, conditional on one being used. This moment condition is

$$M^{12,age}(\boldsymbol{\Theta}) = \frac{E[x_1 x_2 \mid y_1 \neq 2023] - E[x_1 \mid y_1 \neq 2023]\ E[x_2 \mid y_1 \neq 2023]}{\sqrt{\mathrm{Var}(x_1 \mid y_1 \neq 2023)\,\mathrm{Var}(x_2 \mid y_1 \neq 2023)}} - \hat{\rho}^x. \tag{123}$$

Standard errors. We compute standard errors using the delta method. The asymptotic covariance matrix of the parameter estimates is

$$\text{Var}(\hat{\boldsymbol{\Theta}}) \approx (D'\Omega^{-1}D)^{-1}, \tag{124}$$

where $D = \partial \boldsymbol{M}(\boldsymbol{\Theta})/\partial \boldsymbol{\Theta}'$ is the Jacobian of the moment conditions with respect to the parameters, evaluated at $\hat{\boldsymbol{\Theta}}$.

We decompose the moment variance into two components: $\Omega = \Omega^{data} + \Omega^{model}$, and estimate both using bootstrap. The first component, Ω^{data}, captures sampling variation in the empirical targets; we estimate it by resampling observations from the underlying micro-data sources (NVES and NHTS) and recomputing the empirical moments. The second component, Ω^{model}, captures variation in the model-implied moments; we estimate it by resampling products with replacement and recomputing model-implied moments while holding $\hat{\boldsymbol{\Theta}}$ and consumer draws fixed. We treat consumer simulation error as negligible given our large number of consumer draws.

E.2.5 Empirical Moments and Parameter Estimates

Table A8 presents the empirical moments. We construct average prices and ages as z-scores rather than raw quantities to avoid issues caused by mismatches in these distributions between our demographic data sources and the transaction data.

Table A9 presents the parameter estimates. Table A10 presents the Andrews, Gentzkow, and Shapiro (2017) sensitivity matrix, while Table A11 presents the sensitivity matrix transformed into elasticity units.

Table A13 presents demand parameter estimates under two alternative specifications alongside the baseline, and Table A14 reports the implied elasticities and diversion ratios. Column (2) multiplies the new vehicle second choice share moment by 1/2, which is intended to increase the substitutability between new and used vehicles. As expected, the new vehicle random coefficient σ^{new} attenuates substantially, aggregate new vehicle demand becomes considerably more elastic, and diversion from new vehicles to used ones rises sharply. Column (3) multiplies the EV second choice share moment by 2/3, which lowers the EV random coefficient σ^{EV} and in turn makes aggregate EV demand more elastic.

Table A8: **Demand Estimation: Empirical Moments**

Description	(1) Estimate	(2) Standard error
Average firm-level own-price elasticity	-4.686	(-)
EV share among buyers w/ income $>$ \$150k	0.186	(0.003)
New vehicle share among buyers w/ income $>$ \$150k	0.523	(0.039)
Average used purchase age among buyers w/ income $>$ \$150k (z-score)	-0.074	(0.107)
EV share of new second choices, EV buyers	0.674	(0.010)
EV share of used second choices, EV buyers	0.349	(0.044)
New vehicle second choice share	0.911	(0.002)
Correlation between vehicle ages	0.434	(0.017)

Notes: This table presents the empirical moments used in the demand estimation.

Table A9: **Demand Parameter Estimates**

Parameter	Description	(1) Estimate	(2) Standard error
α_0^p	Price response	3.812	0.897
α_0^{new}	New demand intercept	-6.182	2.005
α_0^{age}	Age demand intercept	-0.229	0.040
α_{inc}^{EV}	High-income EV demand shifter	4.346	1.113
α_{inc}^{new}	High-income new demand shifter	3.899	0.828
α_{inc}^{age}	High-income age demand shifter	0.015	0.016
σ^{EV}	EV random coefficient	4.419	0.481
σ^{new}	New random coefficient	3.575	1.074
σ^{age}	Age random coefficient	0.032	0.003
$\rho^{EV,new}$	EV-new random coefficient correlation	0.241	0.260

Notes: This table presents the demand parameter estimates.

Table A10: **Sensitivity Matrix**

	New price elasticity	High-income EV share	High-income new share	High-income avg. age	EV share of new second choices	EV share of used second choices	New second choice share	Age correlation	$\sum$ 1(new) $* \xi$	$\sum$ Age $* \xi$
α_0^p	-0.884	1.002	1.276	0.027	0.181	-0.399	5.705	0.078	0.000	0.000
α_{inc}^{EV}	-0.091	42.372	8.392	0.006	8.643	3.626	0.083	-0.542	0.000	0.000
α_{inc}^{new}	-0.146	-7.918	3.807	0.695	-1.767	2.258	52.073	-1.948	0.000	-0.000
α_{inc}^{age}	-0.011	0.087	-0.016	0.099	0.004	-0.009	0.148	-0.114	0.000	0.000
σ^{EV}	0.043	-18.659	-3.521	0.057	13.346	2.534	2.055	-0.178	-0.000	-0.000
σ^{new}	-0.171	-13.117	-15.342	-0.056	-3.039	4.325	46.468	-2.079	-0.000	-0.000
σ^{age}	0.001	-0.020	-0.003	0.004	-0.004	0.005	-0.005	0.138	-0.000	-0.000
$\rho^{EV,new}$	-0.006	-4.422	-2.680	0.023	-1.019	1.516	-0.309	-0.205	-0.000	-0.000
α_0^{new}	0.227	24.310	22.757	-0.078	6.385	-8.748	-96.044	4.418	-21.071	-0.310
α_0^{age}	0.039	-0.005	-0.063	-0.025	0.008	-0.003	-0.184	-0.228	-0.332	-0.044

Notes: This table presents the sensitivity matrix defined in Andrews, Gentzkow, and Shapiro (2017).

Table A11: **Sensitivity Matrix in Elasticity Units**

	New price elasticity	High-income EV share	High-income new share	High-income avg. age	EV share of new second choices	EV share of used second choices	New second choice share	Age correlation	$\sum$ 1(new) * ξ	$\sum$ Age * ξ
α_0^p	1.087	0.049	0.175	-0.001	0.032	-0.037	1.364	0.009	0.000	0.000
α_{inc}^{EV}	0.098	1.813	1.010	0.000	1.340	0.292	0.017	-0.054	0.000	0.000
α_{inc}^{new}	0.175	-0.378	0.510	-0.013	-0.305	0.202	12.169	-0.217	0.000	0.000
α_{inc}^{age}	3.351	1.052	-0.544	-0.477	0.175	-0.204	8.767	-3.216	0.000	0.000
σ^{EV}	-0.046	-0.785	-0.417	-0.001	2.035	0.200	0.424	-0.017	0.000	0.000
σ^{new}	0.224	-0.682	-2.244	0.001	-0.573	0.423	11.845	-0.252	0.000	0.000
σ^{age}	-0.146	-0.116	-0.049	-0.009	-0.084	0.054	-0.142	1.861	0.000	0.000
$\rho^{EV,new}$	0.117	-3.409	-5.808	-0.007	-2.846	2.196	-1.167	-0.369	0.000	0.000
α_0^{new}	0.172	-0.731	-1.925	-0.001	-0.696	0.495	14.158	-0.310	0.000	0.000
α_0^{age}	0.797	0.004	0.144	-0.008	-0.024	0.005	0.731	0.432	0.000	0.000

Notes: This table presents the sensitivity matrix defined in Andrews, Gentzkow, and Shapiro (2017). For all but the last two columns, we divide each row by the parameter estimate and multiply each column by the empirical moment, so that each cell can be interpreted as the local elasticity of the parameter in the row with respect to the moment in the column.

Table A12: **Parameter Estimates with Alternative Values of the Pure Characteristics Coefficient**

Parameter	Description	(1) $\mu_\epsilon = 3$	(2) $\mu_\epsilon = 5$	(3) $\mu_\epsilon = 7$	(4) $\mu_\epsilon = 12$
α_0^p	Price response	3.936	3.812	3.763	3.774
		(0.915)	(0.897)	(0.907)	(0.969)
α_0^{new}	New demand intercept	-7.038	-6.182	-6.307	-6.675
		(1.404)	(2.005)	(2.154)	(2.480)
α_0^{age}	Age demand intercept	-0.270	-0.229	-0.212	-0.192
		(0.041)	(0.040)	(0.040)	(0.041)
α_{inc}^{EV}	High-income EV demand shifter	4.300	4.346	4.388	4.400
		(1.171)	(1.113)	(1.133)	(1.216)
α_{inc}^{new}	High-income new demand shifter	4.540	3.899	3.847	3.921
		(0.701)	(0.828)	(0.836)	(0.944)
α_{inc}^{age}	High-income age demand shifter	-0.001	0.015	0.023	0.030
		(0.022)	(0.016)	(0.014)	(0.011)
σ^{EV}	EV random coefficient	4.425	4.419	4.428	4.412
		(0.412)	(0.481)	(0.500)	(0.499)
σ^{new}	New random coefficient	4.129	3.575	3.584	3.722
		(0.773)	(1.074)	(1.176)	(1.331)
σ^{age}	Age random coefficient	0.052	0.032	0.023	0.012
		(0.005)	(0.003)	(0.003)	(0.003)
$\rho^{EV,new}$	EV-new random coefficient correlation	0.218	0.241	0.256	0.256
		(0.289)	(0.260)	(0.234)	(0.223)
Aggregate new vehicle price elasticity		-0.79	-0.90	-0.92	-0.90
New car type $\rightarrow$ used ages average diversion ratio		0.09	0.12	0.13	0.12
Age 7 car type $\rightarrow$ other used ages average diversion ratio		0.65	0.79	0.84	0.91

Notes: This table presents the demand parameter estimates with alternative values of the pure characteristics coefficient μ_ϵ.

Table A13: **Demand Parameter Estimates: Alternative Demand Specifications**

Parameter	Description	(1) Baseline	(2) 1/2 new second choice share	(3) 2/3 EV second choice share
α_0^p	Price response	3.812	1.480	3.760
		(0.897)	(0.381)	(0.886)
α_0^{new}	New demand intercept	-6.182	0.392	-7.156
		(2.005)	(0.135)	(4.910)
α_0^{age}	Age demand intercept	-0.229	-0.128	-0.231
		(0.040)	(0.019)	(0.055)
α_{inc}^{EV}	High-income EV demand shifter	4.346	4.383	3.076
		(1.113)	(1.176)	(2.159)
α_{inc}^{new}	High-income new demand shifter	3.899	0.156	4.228
		(0.828)	(0.092)	(2.577)
α_{inc}^{age}	High-income age demand shifter	0.015	-0.017	0.014
		(0.016)	(0.013)	(0.025)
σ^{EV}	EV random coefficient	4.419	3.782	2.280
		(0.481)	(0.567)	(1.690)
σ^{new}	New random coefficient	3.575	0.053	4.222
		(1.074)	(0.067)	(4.731)
σ^{age}	Age random coefficient	0.032	0.030	0.034
		(0.003)	(0.002)	(0.013)
$\rho^{EV,new}$	EV-new random coefficient correlation	0.241	0.436	0.489
		(0.260)	(3.732)	(2.036)

Notes: This table presents demand parameter estimates under alternative specifications. Column (1) is the baseline. Columns (2) and (3) multiply the new vehicle and EV second choice share empirical moments by 1/2, respectively. Standard errors are in parentheses.

Table A14: **Selected Elasticities: Alternative Demand Specifications**

Parameter	(1) Baseline	(2) 1/2 new second choice share	(3) 2/3 EV second choice share
Average new car type price elasticity	-5.24	-4.69	-5.27
Average firm-level price elasticity	-4.69	-4.69	-4.69
Aggregate new vehicle price elasticity	-0.90	-3.92	-0.92
Aggregate new EV price elasticity	-1.96	-1.64	-2.63
Aggregate (new+old) EV price elasticity	-1.59	-0.75	-2.44
New EV $\rightarrow$ new GV diversion ratio	0.57	0.19	0.78
New EV $\rightarrow$ used EV diversion ratio	0.16	0.42	0.07
Used EV $\rightarrow$ used GV diversion ratio	0.54	0.13	0.67
Used EV $\rightarrow$ new EV diversion ratio	0.41	0.80	0.23
New car type $\rightarrow$ used ages average diversion ratio	0.12	0.68	0.12
Age 7 car type $\rightarrow$ other used ages average diversion ratio	0.79	0.65	0.78

Notes: This table presents key elasticities and diversion ratios implied by each demand specification in Table A13. To construct the diversion ratios from new EVs and used EVs, we simulate the effects of raising the price of all new EVs (or used EVs) simultaneously. To construct the diversion ratios from new car types and age 7 car types, we simulate the effects of raising the price of each new (or age 7) car type individually, holding all other prices constant, and report the average diversion ratio across car types, weighting by market shares.

E.3 Market Clearing

E.3.1 Used Vehicle Market Overview

Analogous to the theoretical model in Section 3, used vehicle market clearing requires that supply equals demand for all car types and ages. We now extend this in two ways: allowing sales from fleets to consumers and ensuring market clearing for credit-eligible VINs.

As introduced earlier, there are two price vectors for used vehicles in each year t: the base prices $\boldsymbol{p}_t$ and the eligibility premia $\boldsymbol{p}_t^e$ for credit-eligible vehicles. These prices are determined by two different types of market-clearing equations. First, overall demand must equal supply for each car type and used model year jy in each year t. The overall used vehicle market-clearing condition for each $\{j, a \geq 1\}$ is

$$D_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}_t^e) = S_{jat}^{fleet} + (1 - g_{ja}(p_{jyt})) \cdot \sum_{h=1}^{19} D_{jy,t-h}^{h}. \tag{125}$$

The sum on the right-hand side is the sum of vehicles that were bought previously and are reaching the end of their holding periods. Appendix E.3.3 describes how we construct quantities D_{jyt}^h for years before 2023.

The second type of market-clearing equation is that in counterfactual policy scenarios with the EV tax credit, supply must equal demand for used credit-eligible VINs. Under the IRA, a vehicle was credit-eligible if it is at least two years old and on its first transfer after the IRA passed. Thus, the supply of credit-eligible VINs in year t is fleet sales S_{jat}^{fleet} plus the set of used EVs available for resale (instead of scrappage) that are on first transfer:

$$S_{jyt}^e(p_{jyt} + p_{jyt}^e) = S_{jat}^{fleet} + (1 - g_{ja}(p_{jyt} + p_{jyt}^e)) \cdot \sum_{h=\min(t-2023, t-y)}^{t-y} D_{jy,t-h}^{h} \tag{126}$$

The summation on the right-hand side collapses to a single term (vehicles originally purchased as new) for model years after 2023. For model years before 2023, it includes vehicles that were initially purchased as new as well as those that have already transacted in the used market.

The eligibility premium is weakly positive, since a credit-eligible VIN can't be worth less than an ineligible VIN, but it can't exceed the credit amount, since an eligible consumer would otherwise prefer an ineligible VIN. Thus, there are three possible outcomes for each eligible jyt: (i) excess demand for eligible VINs, with $p_{jyt}^e = \tau_{jyt}$; (ii) supply equals demand for eligible VINs, with $0 \leq p_{jyt}^e \leq \tau_{jyt}$; and (iii) excess supply of eligible VINs, with $p_{jyt}^e = 0$. Considering these three possibilities, the eligible VIN market-clearing condition within each eligible ja is

$$\begin{aligned}
&\textit{Excess demand, max eligibility premium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) > S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies p^e_{jyt} = \tau_{jyt} \\
&\textit{Interior equilibrium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) = S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies 0 \leq p^e_{jyt} \leq \tau_{jyt} \\
&\textit{Excess supply, zero eligibility premium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) < S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies p^e_{jyt} = 0.
\end{aligned} \tag{127}$$

E.3.2 Fleet Sales

This appendix describes how we compute fleet sales S^{fleet}_{jat} for the used vehicle market clearing equations in Appendix E.3.1. While we assume new sales to fleets are exogenous and fixed across simulation years, existing fleet stock idiosyncrasies and model entry imply that S^{fleet}_{jat} is not stationary. Therefore, we must model how fleet scrappage, sales, and stock change across years of the simulation. Let Q_{jat} denote the total stock of vehicles, where Q^{fleet}_{jat} and Q^{ind}_{jat} denote the stock held by fleets and individuals, respectively.

Since we do not model fleet holding times, we model fleet scrap rates as an annual value that is independent of holding time, rather than the end of holding time scrap rates g_{ja} we apply to individuals. We define the annual scrap rate for each car type and age in our observed data as $g^{all}_{ja} = q^s_{ja,2023}/Q_{ja,2022}$, where $q^s_{ja,2023}$ is the total observed scrappage. We then regress annual scrap rates on class and age fixed effects, using the fitted values $\hat{g}^{all}_{ja}$ as fleet scrap rates and winsorizing at 0.

For fleet sales, we compute 2023 fleet sales $q^{fleet}_{ja,2023}$ as the change in the stock of registrations held by individual (not fleet) owners that is not explained by scrappage and new vehicle sales to individuals:

$$q^{fleet}_{ja,2023} = Q^{ind}_{ja,2023} - Q^{ind}_{ja,2022} + q^s_{ja,2023} \cdot Q^{ind}_{ja,2022}/Q_{ja,2022} - D_{j,a=0,2023}, \tag{128}$$

where $Q^{ind}_{ja,2022}$ is individual registrations, $q^s_{ja,2023} \cdot Q^{ind}_{ja,2022}/Q_{ja,2022}$ is scrappage attributable to individual registrations, and $D_{j,a=0,2023}$ is new vehicle sales to individuals in 2023.

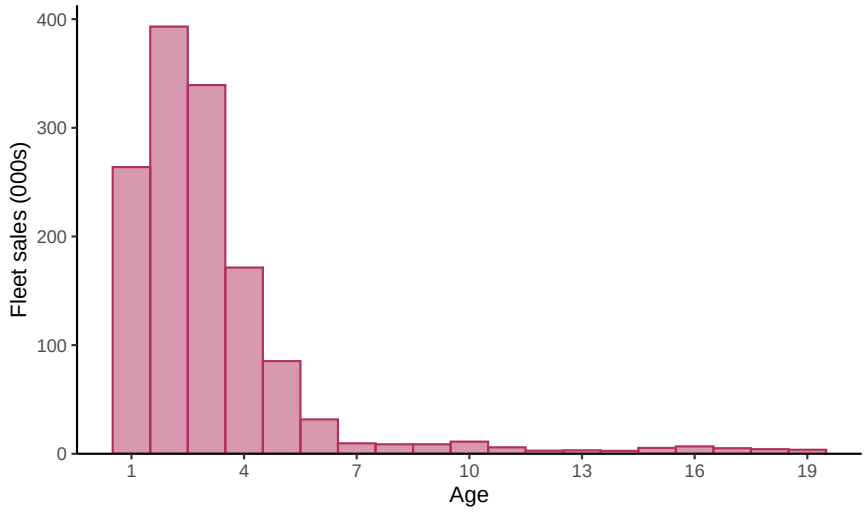
We define a fleet sales rate $q^{fleet,r}_{ja} := q^{fleet}_{ja,2023}/Q^{fleet}_{ja,2022}$ and regress $q^{fleet,r}_{ja}$ on class and age fixed effects. For each year, we then construct $S^{fleet}_{jat} := \widehat{q}^{fleet,r}_{ja} \cdot Q^{fleet}_{j,a-1,t-1}$.

For both fleet sales and scrap rates, we use fitted values instead of the original values to smooth over idiosyncratic observations and to fit ja combinations that are not available in 2023 but will be available in future simulated years.

Using the fitted fleet and scrap rates, we then progress the fleet stock by one year. First, we assume that fleets purchase a fixed quantity of new vehicles $Q^{fleet}_{j,a=0,t}$ equal to the observed new fleet purchases of this car type from October 2022 through September 2023. Second, the existing fleet stock ages by one year with share $\widehat{g}^{all}_{ja}$ being scrapped and S^{fleet}_{jat} vehicles being sold to individuals. For $a > 1$, our yearly stock transition is $Q^{fleet}_{jat} = (1 - \widehat{g}^{all}_{ja}) \cdot Q^{fleet}_{j,a-1,t-1} - S^{fleet}_{jat}$.

Figure A13 presents the resulting sum of $S^{fleet}_{ja,2023}$ by age. The figure shows that most fleet sales are at ages 1–4. This is consistent with our assumption that fleet sales are on their first transfer, so they would be potentially eligible for the used EV tax credit under the IRA.

Figure A13: **Fleet Sales by Vehicle Age**



Notes: This figure shows total fleet sales $S^{fleet}_{ja,2023}$ by age.

E.3.3 2023 Vehicle Ownership by Remaining Holding Time

This subsection describes how we construct $D^h_{ja,t-h}$ for years $t-h<2023$ in Appendix E.3.1, i.e., how we allocate the initial 2023 stock of individual vehicle registrations across consumers with different remaining holding times. Because we do not observe this in the data, we must construct an approximation. To do this, we assume that quantity demanded by holding time in the years before 2023 was as we estimate for 2023, and we simulate market clearing forward to 2023. Since we assume that the maximum holding time is 20 years, we must begin this forward simulation in 2004.

The variable D^h_{jat} denotes purchases of car type j of age a in year t for consumers with holding time h. The total number of car type j vehicles with current age a' that will be sold or scrapped z years later is

$$\Omega^{2023}_{ja'}(z) := \sum_{k=0}^{a'} D^{h=z+a'-k}_{j,a=k,t=2023-a'+k} = \sum_{k=0}^{a'} D^{h=z+a'-k}_{j,a=k,t=2023}, \ \forall\, 0\le a'\le 19,\ 1\le z\le 20-a', \tag{129}$$

where the second equality uses the assumption that D^h_{jat} had been constant for the previous 20 years.

We require that the resulting simulated vehicle holdings match $Q^{ind}_{ja,2023}$, the observed 2023 stock held by individuals:

$$\sum_{z=1}^{20} \Omega^{2023}_{ja}(z) = Q^{ind}_{ja,2023}\ ,\ \forall\, 0\le a\le 19. \tag{130}$$

Accordingly, we rescale the quantity demanded in 2023 as follows:

$$D^h_{ja,t-h} = \frac{Q^{ind}_{ja,2023}}{\sum_{z=1}^{20}\Omega^{2023}_{ja}(z)}\cdot D^h_{ja,2023}. \tag{131}$$

While $D^h_{ja,t-h}$ is sufficient input for the simulation, in order to quantify the "windfall" welfare effects by individual (as described in Appendix E.5), we need a measure of the choice-specific ownership probabilities for individual consumers who bought before 2023 and are now selling. Specifically, define S_{ijat} as the measure of vehicles that were bought before 2023 that will be supplied to the market (i.e., resold or scrapped) in year t of the simulation by consumer i.

Let $Pr_{ija,2023}$ denote the choice probability of car type j with age a in our 2023 estimation for consumer i. Analogously to the above assumption, we assume that $Pr_{ijat}=Pr_{ija,2023}$ for $t<2023$. For $a\ge H_i$, S_{ijat} is then

$$S_{ijat} = \frac{Q^{ind}_{j,a-H_i,2023}}{\sum_{z=1}^{20}\Omega^{2023}_{j,a-H_i}(z)}\cdot Pr_{ij,a-H_i,2023}\cdot \mathbb{1}\{t-H_i<2023\}, \tag{132}$$

and 0 otherwise. The Q/Ω term, which is identical to that in equation (131), serves to scale the estimated demand value to match the observed 2023 vehicle stock.

E.4 Equilibrium Simulation

As described in Section 6.3, the equilibrium is a vector of prices and eligibility premia $\{\boldsymbol{p}_t, \boldsymbol{p}_t^e\}$ for all years t such that consumers correctly forecast new and used vehicle prices and used vehicle markets clear. We solve for the annual (non-stationary) equilibria in each year $t \in \{2024, 2025, ..., 2058\}$. For all years $t \geq 2059$, we assume that consumers believe that vehicle prices $\boldsymbol{p}_t$ will take their steady state values with no tax credits. We index iterations of the solution algorithm by superscripts n, so for example, $\boldsymbol{p}_t^n$ is the vector of year t prices in iteration n.

The solution algorithm has two parts. First, we solve for steady-state equilibrium prices with no tax credits, denoted $\boldsymbol{p}_{ss}$. To do this, we initialize prices $\boldsymbol{p}_{ss}^0$ and quantities $D_{ja,ss}^{h,0}$ with values from a preliminary annual simulation. We then iterate over the following steps until prices converge (i.e., $\boldsymbol{p}_{ss}^n \approx \boldsymbol{p}_{ss}^{n-1}$):

1. set beliefs to prices from previous iteration ($\tilde{\boldsymbol{p}}_{ss}^n = \boldsymbol{p}_{ss}^{n-1}$);
2. find $\boldsymbol{p}_{a>0,ss}^n$ that clear used vehicle markets;
3. find $\boldsymbol{p}_{a=0,ss}^n$ that maximize profits;
4. record quantities $D_{ja,ss}^{h,n}$, which determine future used vehicle supply.

In our model, consumers believe that prices in all years $t \geq 2059$ will take these steady-state values $\boldsymbol{p}_{ss}$.

The second part of the solution algorithm is to find 2024–2058 annual equilibrium prices and eligibility premia, denoted $\{\boldsymbol{p}, \boldsymbol{p}^e\}$. To do this, we initialize $\boldsymbol{p}_t^0$ to the observed 2023 prices, $\forall t$. We then iterate over the following steps until prices converge (i.e., $\tilde{\boldsymbol{p}}^n \approx \tilde{\boldsymbol{p}}^{n-1}$):

1. for all years t, set beliefs to prices and premiums from previous iteration ($\tilde{\boldsymbol{p}}^n = \boldsymbol{p}^{n-1}$, $\tilde{\boldsymbol{p}}^{e,n} = \boldsymbol{p}^{e,n-1}$);
2. for each year $t = \{2024, 2025, ..., 2058\}$:
   (a) find $\boldsymbol{p}_{a>0,t}^n$ and $\boldsymbol{p}_t^{e,n}$ that clear used vehicle markets;
   (b) find $\boldsymbol{p}_{a=0,t}^n$ that maximize profits;
   (c) record quantities D_{jyt}^h, which determine future used vehicle supply.

E.5 Welfare Formulas

Extending the standard logit log-sum formula from Small and Rosen (1981), consumer i's surplus over the holding time for vehicles that could be bought in year t is

$$CS_{it} = \frac{H_i}{\alpha_i^p} \ln \left(\sum_j \exp(L_{ijt}) \right) + C_{i0}, \tag{133}$$

where L_{ijt} is the normalized log-sum over vehicle ages as defined in Section 6.2, and C_{i0} is an unknown constant.

Surprise policy changes cause changes in vehicle resale prices, which affect sellers who hold those vehicles at the time of the policy change. To compute this, define S_{ijat} as the vehicles reaching the end of their holding time in year t for individual i that were part of the initial stock of the simulation. Appendix E.3.3 describes how we compute S_{ijat}. The "windfall" in year t for individual i is

$$\Delta v_{it} = \sum_{ja} S_{ijat} \cdot \left(v_{jat}(p_{jat} + p^e_{jat}) - v_{jat}(p^0_{jat}) \right), \tag{134}$$

where superscript 0 denotes the baseline no subsidy version and $v(\cdot)$ is the resale value net of reconditioning costs. As these vehicles are on the first transfer by definition, we include the credit premium p^e_{jat} (if it exists). Δv_{it} is 0 for our stationary steady state simulations because consumers accurately forecast the effects of the subsidy in equilibrium.

Fleet demand is perfectly inelastic, so the change in fleet surplus will be their change in net spending. We assume fleet new vehicle purchases are at an exogenous price that is fixed across simulations. Therefore, we ignore new fleet purchases in fleet welfare and producer profits. Using our notation for fleets from Appendix E.3.2, fleet welfare can thus be represented as

$$W^{fleet}_t = \sum_j \sum_{a>0} S^{fleet}_{jat}(p_{jat} + p^e_{jat}) + C^{fleet}_t, \tag{135}$$

where S^{fleet}_{jat} is fleet supply net of scrap and C^{fleet}_t is a constant. We assume fleet sales are always on their first transfer and are thus eligible for subsidies. Since we assume fleet scrappage is exogenous, we can ignore scrap payments to fleets, which can be subsumed into the C^{fleet}_t term.

Negative externalities over the holding times of vehicles bought in year t are

$$E_t = \sum_i \sum_j \sum_{y \leq t} Pr_{ijyt} \cdot \left(\mathbb{1}(y = t) \cdot \phi_{nj} + H_i \cdot \phi_{jy} \right), \tag{136}$$

where ϕ_{nj} is the manufacturing externality, which applies only for new vehicles ($y = t$), and ϕ_{jy} is the yearly externality from pollution, accidents, and fiscal externalities, as computed in Appendix E.6.

Total government spending on tax credits in year t is just the sum over vehicles of the tax credit times quantity supplied or demanded (whichever is less, given the possible corner solutions with $p^e_{jyt} = \tau_{jyt}$ or $p^e_{jyt} = 0$):

$$G_t = \sum_{jy} \tau_{jyt} \cdot \min\{S^e_{jyt}, D^e_{jyt}\}. \tag{137}$$

Welfare is the sum of those five terms over time, applying welfare weights w_i to individual consumers:

$$W = \sum_{t=\underline{t}}^{T} \left[\sum_i w_i \left(CS_{it} + \Delta v_{it} \right) + W_t^{fleet} - E_t - G_t \right]. \tag{138}$$

For our stationary equilibrium simulations, we compute yearly total surplus, setting $\underline{t} = T$. For the non-stationary simulations, we compute yearly surplus from each year from $\underline{t} = 2023$ through $T = 2058$, ignoring any possible changes after 2058.

For the simulations with non-equal welfare weights w_i, we construct them inversely proportional to income with a population average weight of 1. Mathematically, $w_i = \frac{1/inc_i}{\sum_i^N (1/inc_i)/N}$.

E.6 Externality Calculation

This appendix provides additional details on how we compute externalities. Table A15 presents a summary of results.

For driving emissions, fiscal externalities, and accident externalities, we calculate these at the vehicle model x MY level and then aggregate to the car type x MY level using 2023 registrations as weights. We obtain data on vehicle curb weights and fuel economy from the 2004–2022 editions of the Ward's Automotive Yearbook.

Manufacturing CO_2 emissions. We use values directly from Kelly et al. (2022), which is broken down into three powertrains: electric-only, gas-only, and hybrid. We assume that the externality for plug-in hybrids is the average of hybrids and electric-only. The larger CO_2 emissions from battery production make the manufacturing externality of electric-only and plug-in hybrids larger than gas-only and hybrids.

CO_2 and local air pollution emissions from driving. For charging emissions from electric-only and plug-in hybrid vehicles, we use regional short-run hourly marginal damages from local pollutants and marginal CO_2 emission rates from Holland et al. (2024).[19] They compute marginal damages using the AP3 model from Muller (2025). We adjust their damages to a \$13.2 million VSL. Taking account of county-level temperature variation and associated electric vehicle battery efficiency, we compute county-level damages per mile of electric vehicle driving. To compute state-level damages per mile, we weight counties by total vehicle miles traveled, following Holland et al. (2016). To aggregate across states, we weight by 2023 new EV sales, which is important because states with higher EV sales have cleaner electricity production, implying a simple average would overstate the marginal pollution rate. We use EV fuel efficiency to compute damages per mile for each model x MY.

For GVs, we compute the damages from tailpipe emissions. For each model x MY, we construct CO_2 emissions per mile using fuel efficiency. For local pollutants, we pull emissions per mile from the EPA's

[19] We use a September 19, 2024 draft of this paper we received directly from the authors.

vehicle test data (US EPA 2024) and the maximum allowable pollution rate for each vehicle's certified bin. We use the midpoint of these values, which we believe is a more accurate measurement of the average lifetime emission rates per mile associated with an aging vehicle driving outside of EPA test conditions. For local pollutants, we apply the county level AP3 marginal damage rates, as in Holland et al. (2024), averaging to the state level weighting by vehicle miles traveled and then averaging to the national level weighting by new 2023 GV sales. We assume that 63 percent of plug-in hybrid miles are on gasoline and 37 percent are on electricity, following Plötz et al. (2020). Table A15 shows that local air pollution externality is much higher for EVs, while the driving CO_2 externality is larger for GVs.

Accident externalities. We follow Anderson and Auffhammer (2014) in calculating the increase in crash fatalities due to driving a vehicle compared to the lightest model in our dataset (the 2015 gas-only Smart Fortwo, which weighs 1,822 pounds). Specifically, increased fatalities is the product of the accident probability and the incremental death probability based on the curb weight of the vehicle, where we take the latter from Anderson and Auffhammer (2014). We compute the accident probability as the total accidents in 2021 (NHTSA 2023) divided by the total vehicle registrations in 2021 (NHTSA 2022). The accident externality from driving a heavier vehicle is then the increased fatalities multiplied by a $13.2 million value of statistical life (VSL) from US Department of Transportation (2024). As shown in Table A15, the extra weight profile of PHEVs and EVs yields a larger accident externality.

Energy pricing externalities. For EVs we account for utility-specific markups on residential electricity above private marginal costs, as calculated by Borenstein and Bushnell (2022). We weight utilities in a state by electricity sales and then weight the states by the share of new EV sales in 2023. The resulting weighted average markup is 12 cents per kWh. For GVs we utilize federal and state fuel taxes, weighting by 2023 new GV sales. The resulting weighted average gas tax is 64 cents per gallon. The fiscal externality for a particular model depends on its fuel usage per mile (either electricity or gas), miles traveled, and the weighted markup or tax. Table A15 shows that fiscal externalities are larger for electricity fueled vehicles.

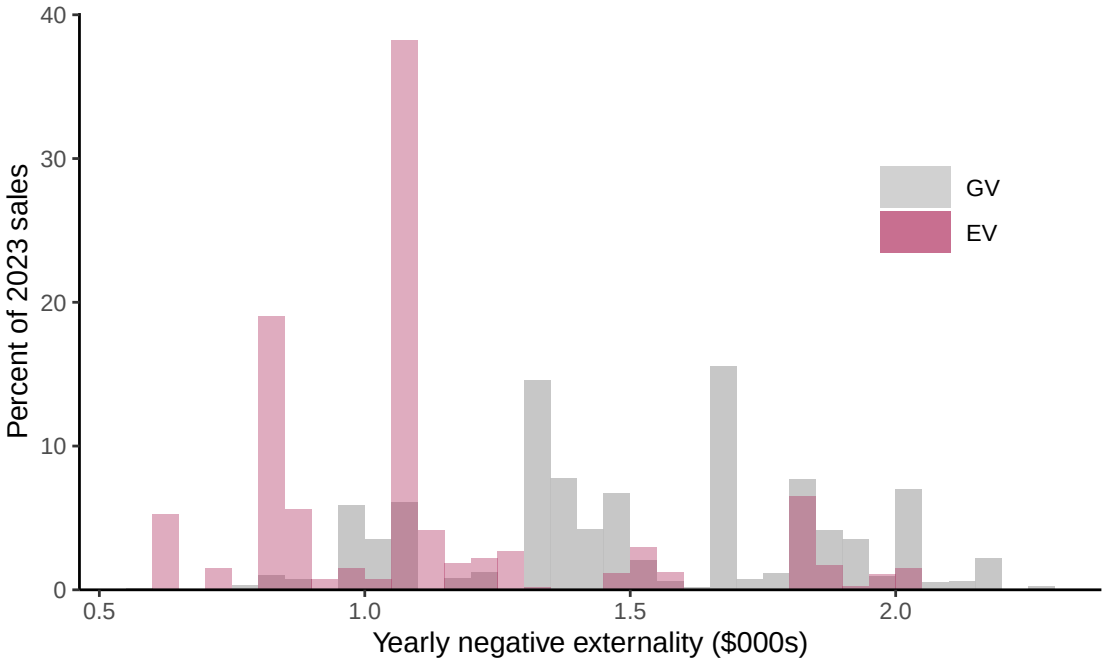
While the U.S. and other countries provide uniform subsidies for electric vehicles, there is substantial variation in externalities *within* powertrains. There is thus significant overlap in the distributions of externalities for EVs versus GVs, as shown in Figure A14. For EVs, the 10th and 90th percentiles of yearly negative externalities are $800 and $1,800. For GVs, the 10th and 90th percentiles are $1,000 and $2,000. This means that in our model with no other corrective policies, heterogeneous vehicle-specific taxes could substantially increase total surplus relative to uniform EV subsidies.

Table A15: **Monetized Negative Externalities by Powertrain for New Vehicles ($)**

Externality	(1) Electric-only	(2) Plug-in hybrid	(3) Hybrid	(4) Gas-only
Manufacturing CO2	2,902	2,368	1,835	1,813
Total yearly externalities	1,018	1,521	1,215	1,551
Driving local pollutants	40	40	19	28
Driving CO2	430	829	608	1,021
Excess weight in accidents	963	1,060	746	766
Energy pricing externality	-414	-409	-157	-265
Expected lifetime externality	19,535	27,210	21,685	27,146

Notes: This table presents externalities by powertrain for new vehicles, weighting models by 2023 sales. Manufacturing CO_2 is a one-time cost in units of $, while the other categories are in $/year.

Figure A14: **Distribution of Yearly Externalities Across Car Types**



Notes: This figure presents the distribution of yearly negative externalities across new car types, weighting by market share, separately for gasoline vehicles (including hybrids) and electric vehicles (including plug-in hybrids).

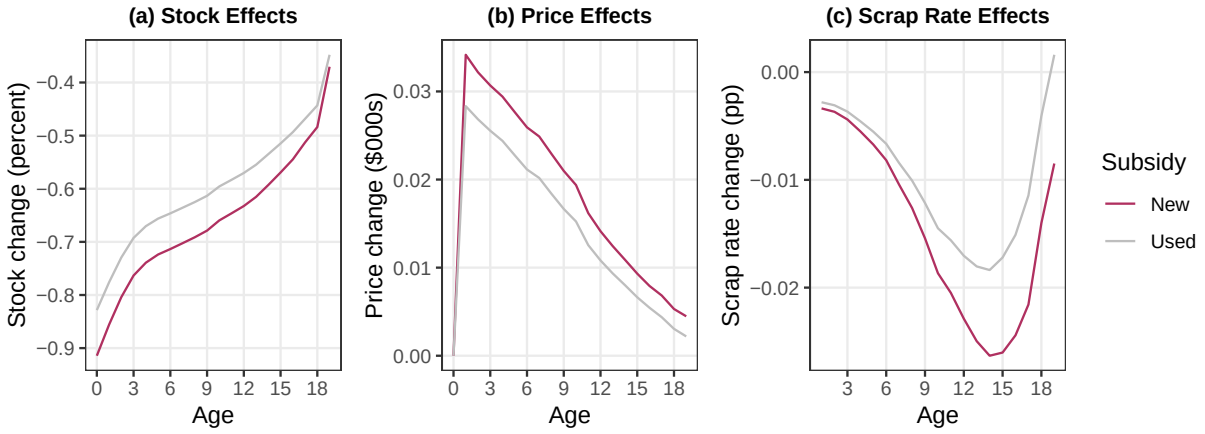
F Counterfactual Simulation Appendix

Table A16: **Effects of EV Subsidies in Stationary Equilibrium with Alternative Parameter Assumptions**

	Baseline		1/2 new second choice share		1/2 EV second choice share		Fixed scrap rate	
	(1) New subsidy	(2) Used subsidy	(3) New subsidy	(4) Used subsidy	(5) New subsidy	(6) Used subsidy	(7) New subsidy	(8) Used subsidy
New EV subsidy ($000s)	2	0	2	0	2	0	2	0
Used EV subsidy ($000s)	0	2	0	2	0	2	0	2
Income limit	✗	✗	✗	✗	✗	✗	✗	✗
Price limit	✗	✗	✗	✗	✗	✗	✗	✗
Panel (a): Market Effects								
%ΔNew EV sales	2.94	2.36	0.16	-0.28	3.79	3.07	2.04	1.90
%ΔNew + used EV stocks	0.98	0.92	0.86	1.05	1.79	1.87	0.98	0.76
ΔAverage EV lifetime (years)	-0.32	-0.23	0.13	0.23	-0.31	-0.17	-0.16	-0.18
ΔNew EV average rent ($000s/year)	-0.24	-0.20	-0.12	-0.11	-0.15	-0.12	-0.19	-0.17
ΔUsed EV average rent ($000s/year)	-0.10	-0.10	-0.13	-0.12	-0.10	-0.10	-0.11	-0.10
ΔAge 1-9 EV average price ($000s)	-1.39	-0.14	-1.52	-0.15	-1.53	0.05	-1.50	-0.19
ΔAge 10-19 EV average price ($000s)	-0.68	-0.51	-0.69	-0.37	-0.73	-0.47	-0.79	-0.55
%ΔAge 1-9 EV scrap rate	4.14	0.95	3.98	0.58	4.38	0.25	0.00	0.00
%ΔAge 10-19 EV scrap rate	4.05	3.27	4.42	3.15	4.48	3.25	-0.00	0.00
Panel (b): Welfare Relative to No Subsidy								
ΔConsumer surplus ($millions/year)	1,806.39	1,875.26	1,981.81	1,997.49	1,858.78	1,911.45	1,798.66	1,868.41
Inc ≥$150k: ΔCS ($/consumer-year)	78.45	70.00	93.32	83.72	171.98	156.54	73.44	67.45
Inc >$150k: ΔCS ($/consumer-year)	40.33	38.40	41.30	37.54	3.44	3.77	42.91	39.60
ΔNegative externality ($millions/year)	-51.00	-54.00	-25.80	-30.56	-139.56	-134.84	-77.72	-67.51
ΔDriving externality ($millions/year)	-96.90	-87.57	-50.41	-43.54	-191.01	-172.30	-101.26	-90.01
ΔManufacturing externality ($millions/year)	45.90	33.57	24.60	12.98	51.45	37.46	23.54	22.50
Subsidy spending ($millions/year)	1,831.15	1,896.90	2,003.09	2,019.76	1,890.90	1,942.37	1,815.08	1,881.91
ΔTotal surplus ($millions/year)	26.24	32.36	4.53	8.28	107.43	103.92	61.30	54.00
ΔWelfare-weighted total surplus ($millions/year)	-209.49	-159.07	-329.57	-304.51	-1,244.41	-1,119.80	-102.33	-99.61
MVPF	1.01	1.02	1.00	1.00	1.06	1.05	1.03	1.03
Welfare-weighted MVPF	0.89	0.92	0.84	0.85	0.34	0.42	0.94	0.95

Notes: This table presents the effects of new and used EV subsidies in stationary equilibrium relative to zero EV subsidies. Columns 1 and 2 reproduce the baseline simulations from columns 1 and 4 from Table 6. Columns 3 and 4 present simulations using the demand estimates from column 2 of Table A13, which multiplied the new vehicle second choice share empirical moment by 1/2. Columns 5 and 6 present simulations using the demand estimates from column 3 of Table A13, which multiplied the EV second choice share empirical moment by 1/2. Columns 7 and 8 present simulations with perfectly inelastic scrap rates fixed at their baseline values. Rents include subsidies for eligible consumers. Rent effects are averages across consumers, weighting by baseline choice probabilities. The marginal value of public funds (MVPF) is $(\Delta\text{Consumer surplus} - \Delta\text{Negative externality (excluding gas tax revenue)})/(\text{Subsidy spending} - \Delta\text{Gas tax revenue})$. The "welfare-weighted" total surplus and MVPF weight consumers by 1/income, holding constant the average consumer's weight.

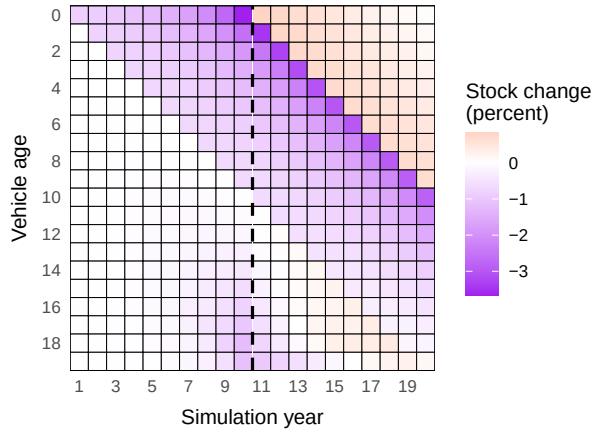
Figure A15: **Market Effects of EV Subsidies on Gasoline Vehicles in Stationary Equilibrium**



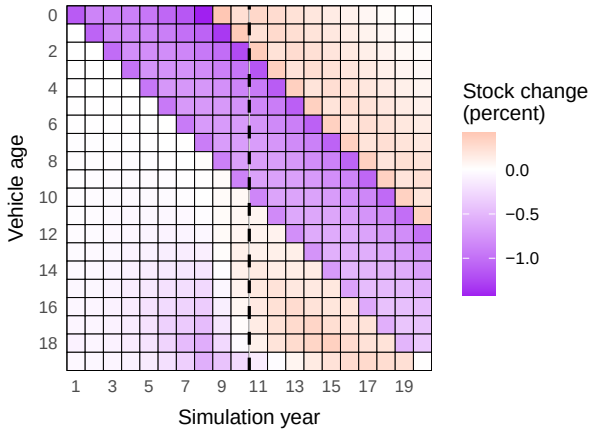
Notes: These figures present the effects of $4,000 new or used EV subsidies on GV stocks, prices, and scrap rates in stationary equilibrium by age. Price effects are averages across consumers, weighting by baseline choice probabilities.

Figure A16: **Market Effects of EV Subsidies on Gasoline Vehicles in Non-Stationary Equilibrium**

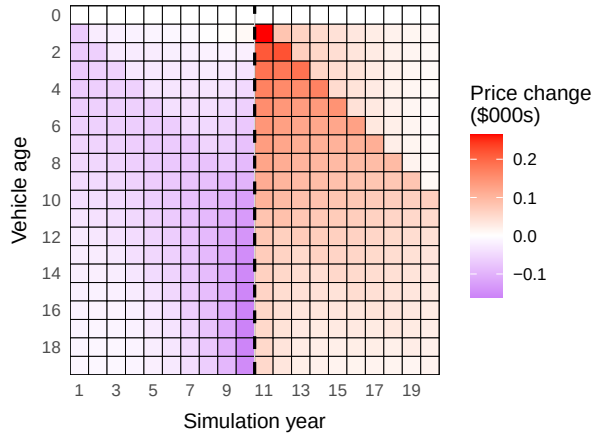
(a) **New Subsidy: Stock Effects**



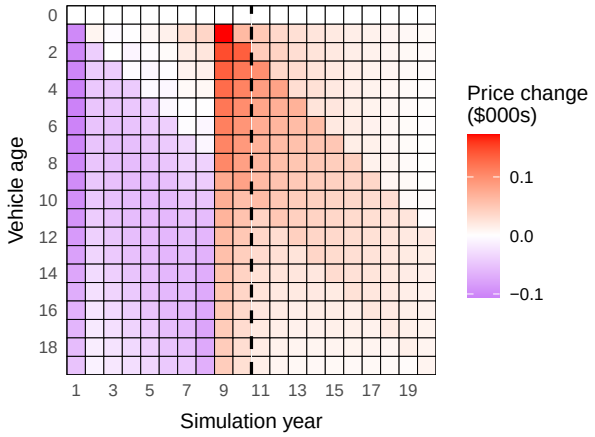
(b) **Used Subsidy: Stock Effects**



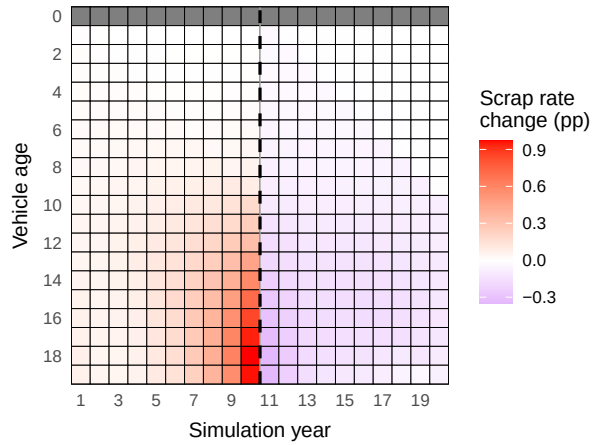
(c) **New Subsidy: Price Effects**



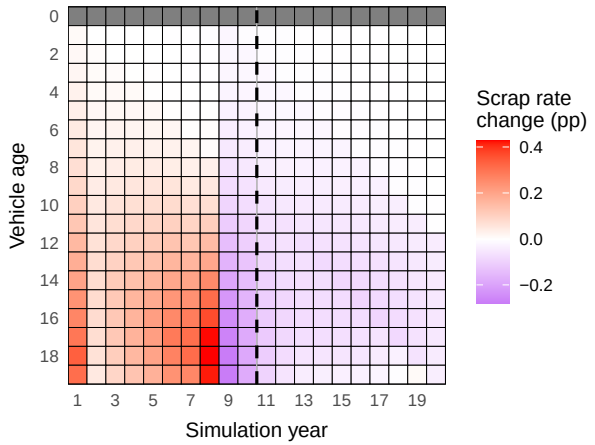
(d) **Used Subsidy: Price Effects**



(e) **New Subsidy: Scrap Rate Effects**



(f) **Used Subsidy: Scrap Rate Effects**



Notes: These figures present the effects of $4,000 new or used EV subsidies on GV stocks, prices, and scrap rates in non-stationary equilibrium by year. At the beginning of simulation year 1, the subsidies are introduced unexpectedly. From that point, consumers know that the subsidies will be available in years 1–10. Price effects are averages across consumers, weighting by baseline choice probabilities.

F.1 Imperfect Competition

This appendix presents stationary equilibrium simulation results under a limited model of imperfect competition: keeping prices exogenous, but inferring vehicle markups and marginal costs using a Nash-Bertrand pricing assumption. We assume that the numeraire good has zero markup; changing this assumption would change the total surplus effects of EV subsidies in proportion to the change in numeraire spending.

F.1.1 Setup

Each firm f produces a set of new vehicles $\mathcal{J}_f$, each with constant marginal cost c_j. We assume $\mathcal{J}_f$ (i.e., the vehicles and their characteristics), p_j, and c_j do not change across years, staying fixed at their 2023 values. The firm sets prices in $t = 0$ assuming a constant choice set and time horizon to T. We assume no time discounting, consistent with the assumption elsewhere in the paper. Firm f's profit function is the sum of profits over vehicles they make ($j \in \mathcal{J}_f$) and over all years:

$$\pi_f = \sum_{t=0}^{T} \sum_{j \in \mathcal{J}_f} (p_{0jt} - c_j) D_{0jt}(\mathbf{r}), \tag{139}$$

where $\mathbf{r}$ is the vector of vehicle rents.

The firm FOC with respect to the price of vehicle k in $t = 0$ is then

$$\frac{d\pi_f}{dp_{0k0}} = 0 = D_{0k0}(\mathbf{r}) + \sum_{t=0}^{T} \sum_{j \in \mathcal{J}_f} (p_{0jt} - c_j) \frac{dD_{0jt}}{dp_{0k0}}. \tag{140}$$

This is the classic equation which says that the change in profits can be decomposed into the effects from inframarginal units today and the change in the marginal unit of demand times the markup across all periods.

By the definition of the total derivative and recognizing that used vehicles prices in period t are functions of new prices in period $t = 0$, we can express equation (140) as

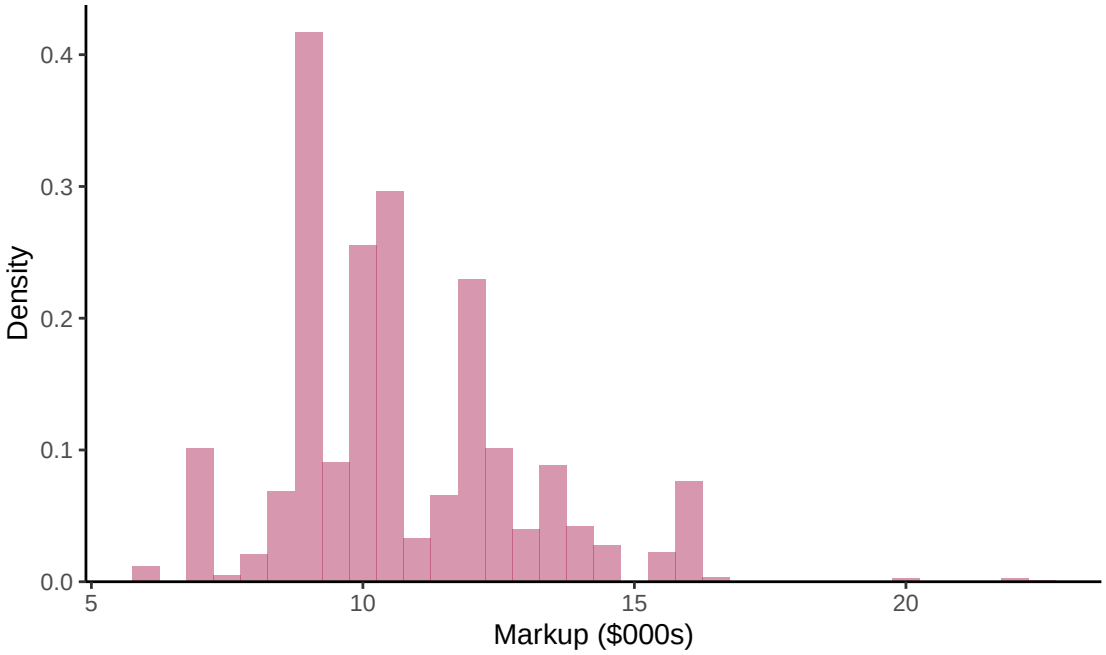
$$\begin{aligned} \frac{d\pi_f}{dp_{0k0}} = 0 = D_{0k0}(\mathbf{r}) &+ \sum_{j \in \mathcal{J}_f} \sum_{j' \in J} \sum_{a} (p_{0j0} - c_j) \left[\frac{\partial D_{0j0}}{\partial r_{aj'0}} \frac{dr_{aj'0}}{dp_{0k0}} \right] \\ &+ \sum_{j \in \mathcal{J}_f} \sum_{t=1}^{T} (p_{0jt} - c_j) \left[\frac{\partial D_{0jt}}{\partial v_{0jt}} \frac{dv_{0jt}}{dp_{0k0}} + \sum_{j' \in J} \sum_{a>0} \frac{\partial D_{0jt}}{\partial r_{aj't}} \frac{dr_{aj't}}{dp_{0k0}} \right]. \end{aligned} \tag{141}$$

The first line of equation (141) is the change in profits in period 0, while the second line is the dynamic effects due to demand changes in future periods.

We implement this equation by making two assumptions. First, we assume the cross-model effects are zero, so $dr_{aj't}/dp_{0j0} = 0$ if $j' \neq j$. Second, implementing the full dynamic consideration given in the second line of equation (141) would be very difficult due to the variation in consumer holding time—it would necessitate solving a computationally intensive recursive problem where we must solve for price derivatives and equilibrium by year. Thus, we approximate the steady-state effect by assuming proportional rent change that occurs in the same period as the new price adjustment.

Inferred marginal cost. As in Berry, Levinsohn, and Pakes (1995), we infer marginal costs by inverting each firm's profit function at the observed 2023 prices. The sales-weighted average implied markup is \$9,500, or 21 percent of the price. Appendix Figure A17 presents the distribution of implied markups across vehicles.

Figure A17: **Distribution of Implied Markups in 2023**



Notes: This figure presents the distribution of implied markups $p_j - c_j$ across car types j, weighting by market share.

F.1.2 Results

Table A17 presents our basic stationary equilibrium results allowing for markups. Panel (a) reprints the total surplus and MVPF results from Table 6 for comparison. Since we assume that vehicle prices are unchanged, the only changes are the newly-added profits and the resulting welfare and MVPF estimates. Panel (b) presents those updates. The key conclusion is that allowing markups on vehicles (although not on

the numeraire) increases the welfare gains from EV subsidies. The same qualitative difference applies to all of our other results tables.

Table A17: **Effects of EV Subsidies in Steady-State Equilibrium, with Markups**

	New subsidy			Used subsidy		
	(1)	(2)	(3)	(4)	(5)	(6)
New EV subsidy ($000s)	4	4	4	0	0	0
Used EV subsidy ($000s)	0	0	0	4	4	4
Income limit ($000s)	–	150	150	–	150	150
Price limit ($000s)	–	–	50	–	–	25
Panel (a): Welfare Relative to No Subsidy with Perfect Competition						
ΔTotal surplus ($millions/year)	185	-64	-5	208	-46	35
ΔWelfare-weighted total surplus ($millions/year)	-1,473	231	64	-1,238	-1,096	-406
MVPF	1.04	0.96	0.99	1.04	0.99	1.02
Welfare-weighted MVPF	0.69	1.14	1.11	0.74	0.76	0.78
Panel (b): Welfare Relative to No Subsidy With Exogenous Markups						
ΔProfit ($millions/year)	296	78	-8	154	159	4
ΔGV profit ($millions/year)	-838	-453	-201	-767	-764	-242
ΔEV profit ($millions/year)	1,134	531	193	921	923	245
ΔTotal surplus ($millions/year)	481	14	-13	363	113	39
ΔWelfare-weighted total surplus ($millions/year)	-1,177	309	56	-1,084	-938	-402
MVPF	1.10	1.01	0.98	1.08	1.02	1.02
Welfare-weighted MVPF	0.75	1.19	1.10	0.77	0.80	0.78

Notes: This table presents the effects of new and used EV subsidies in stationary equilibrium relative to zero EV subsidies. Panel (a) reproduces results from Table 6, assuming zero markups. Panel (b) presents the updated results with exogenous markups. Rents include subsidies for eligible consumers. Rent effects are averages across consumers, weighting by baseline choice probabilities. The marginal value of public funds (MVPF) is $(\Delta\text{Consumer surplus} - \Delta\text{Negative externality (excluding gas tax revenue)})/(\text{Subsidy spending} - \Delta\text{Gas tax revenue})$. The "welfare-weighted" total surplus and MVPF weight consumers by 1/income, holding constant the average consumer's weight.