The Economics of New versus Used Electric Vehicle Subsidies

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Abstract

We study the economics of used electric vehicle (EV) subsidies, which have been implemented in the U.S. and eight other countries in hopes of moderating the potential regressivity of new EV subsidies. We show theoretically that under certain conditions, new and used EV subsidies are actually economically equivalent due to equilibrium price adjustments. We then estimate the incidence of recent U.S. used EV tax credits using unique microdata and a novel bunching estimator. Strikingly, we find that the credits had almost no effect until 2024, when they could be paid out immediately at the dealership. Finally, we use a new structural model to compare the dynamic effects of new versus used EV subsidies. In the model, used EV subsidies are no less regressive than new EV subsidies, new EV subsidies with buyer income limits substantially increase progressivity *and* the marginal value of public funds, and delaying the age at which a used EV qualifies for the tax credit improves efficiency by reducing scrappage.

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" (Kresge Foundation 2024, World Economic Forum 2024) and these concerns have shaped provisions 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 energy efficiency, solar panels, 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 a central 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 EV subsidies can involve significant government spending: before the IRA's EV tax credits were rescinded in late 2025, they were forecasted to cost $70 to $390 billion over 10 years (CRFB 2023; Bistline, Mehrotra, and Wolfram 2023). But in the U.S., the median new EV buyer in 2023 had household income of about 2.5 times 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 U.S. IRA) included buyer income limits, vehicle price limits, and/or subsidies for purchasing *used* EVs. Policy makers and analysts have argued that used EV subsidies are more progressive, because lower-income people buy more used cars.[1]

This paper provides a comprehensive evaluation of the efficiency and equity of new versus used EV subsidies, using a theoretical model, a novel bunching estimator of short-term incidence, and a novel dynamic structural model of long-term effects on new and used vehicle markets. Our empirical work focuses on the tax credits under the U.S. IRA, but the economic lessons are relevant for state and national governments worldwide. Our analyses are made possible by a unique collection of confidential data, including transaction-level microdata covering 44 percent of nationwide dealership sales and large-scale second-choice survey data from the National Vehicle Experience Survey.

We begin with a stylized theoretical model to fix ideas. In the model, firms sell new EVs in symmetric imperfect competition. Vehicles live for either one or two periods ("new" and "used") before being scrapped. Consumers choose between new EVs, used EVs, and the outside option, which we think of as a gas vehicle (GV). EVs impose a smaller negative externality than the outside option. To correct this, the government can subsidize new and/or used EV purchases.

Resale market equilibrium effects at least partially offset the differing statutory incidence of new and

[1] In 2021, U.S. Senator Alex Padilla co-sponsored a bill to offer used EV tax credits on the grounds that they would "support our working families by ensuring equitable access" to EVs (Gomez 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 important for lower-income consumers.

used EV subsidies: new EV subsidies increase resale market quantities and thus decrease resale prices (benefiting used EV buyers), while used EV subsidies increase resale prices (benefiting new EV buyers). With fully inelastic scrappage, this offset is exact: new and used EV subsidies are *equivalent* in steady state.

In the model, the total surplus-maximizing policy is a Pigouvian subsidy: subsidize new EVs by the externality reduction plus the markup, and subsidize used EVs by the externality reduction. With fully inelastic scrappage, the equivalence result implies a continuum of optimal linear combinations of new and used EV subsidies. With elastic scrappage, however, there is an efficiency rationale for used EV subsidies: they keep EVs from being scrapped suboptimally early.

In a Diamond (1975)-style model with higher social marginal welfare weights on lower-income consumers, and assuming that lower-income consumers have stronger preferences for used EVs, the optimal subsidy combination does not necessarily tilt toward used EV subsidies. This is because even though the statutory incidence of used EV subsidies is on the lower-income group, the resale market equilibrium effects make the economic incidence ambiguous. In fact, we show that the inequality-averse social planner prefers income-limited *new* EV subsidies over either universal or income-limited used EV subsidies, because used EV subsidies benefit all of the (relatively wealthy) new EV buyers by increasing resale prices, while the income-limited new EV subsidy benefits only lower-income new EV buyers.

The theory offers a new example of the classic idea that equilibrium price adjustments drive a wedge between statutory and economic incidence. But to what extent do market prices actually adjust to used EV tax credits? To measure this, we exploit another equity-focused component of the IRA's used EV tax credits: the credit was only available on transactions priced at $25,000 or less. We show that this price cap generates slight bunching in the distribution of used EV transaction prices in 2023, and substantial bunching in 2024 and 2025. Intuitively, since larger equilibrium price changes should be associated with more bunching below the $25,000 price limit, we should be able to use the amount of excess mass to identify the incidence of the tax credit.

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 prices in 2023. The price shift increases 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. We discuss various explanations for this result, including the salience of receiving money now instead of later. Overall, these results underscore the importance of tax credit *implementation*, not just the *amount*.

We develop a novel dynamic structural model that generalizes the theoretical framework to allow quantitative predictions in a more realistic setting. The choice set includes all light-duty EVs and GVs aggregated by brand, body style, powertrain, and age (from new to age 19). Firms set new vehicle prices in Nash-Bertrand equilibrium. Equilibrium used vehicle market are such that demand equals scrappage-adjusted

supply for each model and age. Consumers have logit demand with random coefficients, allowing for heterogeneous preferences by income and across new versus used vehicles and EVs versus GVs. Also, we use a pure characteristics framework (Berry and Pakes 2007) to capture substitution across ages within a model. One key innovation is to model a realistic distribution of the number of years consumers hold their vehicles before reselling. This allows us to track which EVs are being resold for the first time, which the IRA tax credits required in order to disallow gaming of the credit by repeatedly reselling a given vehicle.

Our first counterfactual simulations are in steady state equilibrium, where vehicle prices and quantities remain constant over time. In the steady state, a $4,000 new EV subsidy decreases average used EV prices by about $2,000, while a $4,000 used EV subsidy increases average used EV prices by about $2,500, illustrating how used EV subsidies benefit new EV buyers through higher resale values. We compute the marginal value of public funds (MVPF) using Pareto weights inversely proportional to household income. The model predicts that a new EV subsidy with a $150,000 income limit achieves a Pareto-weighted MVPF of 1.34, while used EV subsidies with (without) similar targeting achieve lower MVPFs of 1.02 (0.98). Consistent with the earlier theoretical result, this shows that since used EV subsidies benefit all new EV buyers (who are relatively wealthy), equity goals are best achieved through explicit income limits instead of through subsidizing used EVs, even though used EV buyers have lower incomes.

We then consider optimal policy designs in steady state equilibrium. Given our externality calculation, the socially optimal new and used EV subsidies are $5,000 and $0, respectively. While theory suggests that used EV subsidies can improve efficiency by reducing suboptimally early scrappage, this channel is limited in practice because most vehicles eligible under the IRA are relatively young and unlikely to be scrapped. In practice under the IRA, used EVs are only eligible for tax credits on their first transfer, which is before age 10 for 75 percent of vehicles. Since EVs under age 10 have much lower scrap rates than older EVs, the IRA's used EV tax credits have more limited effect on scrappage in our model. In a counterfactual simulation where used EVs are only eligible on their first transfer after age 10, the socially optimal new and used EV subsidies are both $5,000. Welfare increases further under first best policy that internalizes both externalities and markup distortions at the vehicle and age level: subsidies for new vehicle purchases reflect equilibrium markups, while usage taxes vary with vehicle-specific externalities over the vehicle's lifetime.

Finally, we simulate counterfactuals in a non-stationary equilibrium that approximates the IRA design as a temporary policy lasting 10 years. While many steady state results carry over, an important additional distinction arises in the timing of policy effects. New EV subsidies generate *forward* benefits: a subsidy in period t increases EV adoption today, which raises future EV stock and affects used EV prices in later periods. These benefits persist even after the policy expires. In contrast, used EV subsidies generate *backward* benefits through resale value expectations: a subsidy in period t raises expected resale prices, which feeds back into demand for newer vehicles in earlier periods. When policies are temporary, these backward effects are truncated, making used EV subsidies less effective and generating MVPFs lower than one.

Our analyses should be interpreted with several caveats. First, our structural model, like any model, makes simplifying assumptions. For example, we assume that the length of time consumers hold their vehicles before reselling is exogenous instead of potentially affected by vehicle resale prices. Second, we also simulate a slightly simplified version of the EV tax credits implemented under the IRA, for example by ignoring the differences in income limits for people who are single versus married filing jointly. Our goal was to capture the primary economic features of policy questions around equity in EV subsidies while avoiding additional complexity around secondary issues.

A final caveat is that our conceptual framework assumes that the government cannot fully address distributional concerns through more progressive income taxation. Put differently, we apply the 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.[2] Important papers by Nehiba and Tyndall (2024) and Berman, Hickok, and Nguyen (2025) study other facets of the used EV tax credits.[3] Second, we extend the broader literature on environmental policy in auto markets.[4] Third, we extend the literature on Inflation Reduction Act evaluations.[5].

[2]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).

[3]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. Our work is different in that we study actual transaction prices using a bunching estimator, which is more precise than our difference-in-differences estimator and unaffected by potentially confounding vehicle market trends. Berman, Hickok, and Nguyen (2025) present theoretical and structural analyses of used EV tax credits, including a proposition analogous to our equivalence result. Their models focus on endogenizing vehicle owners' choice of when to resell their vehicles. Our work is different in that we assume that holding times are exogenous; this assumption is consistent with our empirical estimates in Appendix Table A4. This simplification makes it easier for our structural model to include other potentially important features that Berman, Hickok, and Nguyen (2025) do not consider, including imperfectly competitive vehicle supply and a demand system with random coefficients that generate realistic substitution patterns across EVs versus GVs and new versus used vehicles.

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

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

Fourth, we connect to the literature on distributional effects of energy policy and other corrective taxes.[6] Fifth, our finding of increased effects of tax credits after dealership transfer in 2024 may relate to the literature on tax salience.[7] Finally, our structural model builds on other structural models of resale markets for autos and other goods.[8]

Our key contribution is to provide a comprehensive evaluation of used EV subsidies, with novel empirics using U.S. data that provide broadly applicable economic lessons. A key part of this contribution is results that reframe the popular rationale for used EV subsidies: contrary to the current narrative, they are less progressive than means-tested new EV subsidies, and instead potentially helpful for economic efficiency by reducing scrappage–but only if broadly available for older vehicles that are actually at risk of scrappage, unlike in the U.S. IRA's design.

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

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). And 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).

New EV buyers are relatively wealthy: in the U.S. in 2023, the median new EV buyer had household income of $169,000, 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. Appendix A presents details.

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 available

[6] 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 other corrective taxes includes Gruber and Kőszegi (2004) and Goldin and Homonoff (2013) on cigarette taxes and Allcott, Lockwood, and Taubinsky (2019a, 2019b) on soda taxes.

[7] 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).

[8] 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), Gowrisankaran and Rysman (2012) on other markets.

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.

While these 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 Biden Administration's 2022 Inflation Reduction Act (IRA) 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 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. To be eligible, the vehicle had to be at least 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; the IRS enforced this by tracking the Vehicle Identification Numbers (VINs) of vehicles claiming the credit. This prevented people from gaming the credit by repeatedly trading the same vehicle.

The used EV tax credit also has 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 made 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.

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. Reported subsidy amounts are the maximum offered. 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. 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.

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 derive comparative statics and optimal policies.

We let t index periods. In the model, 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). When produced, EVs have a one-time production externality ϕ_n relative to the GV. For each period of use, EVs also reduce negative externalities by ϕ relative to the GV. The government offers new and used vehicle purchase subsidies $\{\tau_{nt}, \tau_{ut}\}$, which are paid to buyers and financed through lump-sum taxes.

Firms produce new vehicles at constant marginal cost c and sell them at price p_n in symmetric imperfect competition. Following Genesove and Mullin (1998) and Weyl and Fabinger (2013), we assume markups are governed by a "conduct parameter" $\theta := \frac{p_n - c}{p_n}\epsilon_D$, where $\epsilon_D > 0$ is the new vehicle market demand elasticity.

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.

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

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

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

There is a set of consumer income types indexed $i \in I$. Define $e_i \in \{1, 0\}$ as an indicator for whether type i is eligible for the subsidies. (We assume that eligibility conditions do not differ between the new and used subsidies.) 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 $D_{iat} := D_{ia}(\tilde{r}_{int}, r_{iut})$ for each age. Market demand functions are then $D_{at} = \sum_i D_{iat}$. 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 slope.

An equilibrium is a set of prices $\{p_{nt}, p_{ut}\}$ such that (i) firms and consumers optimize, generating the conduct parameter and demand functions described above, (ii) new vehicle buyers correctly forecast the

resale price, i.e. $\tilde{p}_{u,t+1} = p_{u,t+1}$, and (iii) the used vehicle market clears, i.e. $D_{ut} = (1-g)D_{n,t-1}$. Much of our analysis focuses on the steady state, defined as $p_{at} = p_{a,t+1} = p_a$, for $a \in \{n, u\}$.

3.2 Steady-State Comparative Statics

We begin with comparative statics: how new and used EV tax credits affect prices, quantities, and rents. For this subsection, it is expositionally helpful to assume that all consumer types i have identical demand functions and differ only on eligibility e_i. Define μ as the share of consumers eligible for the subsidies. We can now write average new and used rental prices as $\tilde{r}_{nt} = p_{nt} - \mu\tau_{nt} - \tilde{v}_{t+1}$ and $r_{ut} = p_{ut} - \mu\tau_{ut} - r^s$, respectively, and aggregate demand $D_{at} \coloneqq D_a(\tilde{r}_{nt}, r_{ut})$.

Define $D'_a < 0$ as the own-price response: the derivative of D_{at} with respect to age a average rental price r_a. Under quasilinear utility, Slutsky symmetry implies that the cross-price responses are equal. Define $D'_c > 0$ as the cross-price response: the derivative of D_{at} with respect to the other age's average rental price. Throughout this subsection, we assume the cross-price response D_c is not too large relative to the own-price response D_a: specifically, $D'_c < (1-g)|D'_a|$. Substantively, this just means that there is at least some substitution between EVs and GVs (the outside good).

3.2.1 Price and Quantity Effects

Proposition 1 presents comparative statics on the effects of marginal subsidy changes on steady-state equilibrium prices and quantities.

Proposition 1. *The steady-state equilibrium price effects are*

$$\frac{dp_n}{d\tau_n} \geq 0, \quad \frac{dp_n}{d\tau_u} \lessgtr 0$$
$$\frac{dp_u}{d\tau_n} \leq 0, \quad \frac{dp_u}{d\tau_u} \geq 0.$$

The quantity effects are

$$\frac{dD_n}{d\tau_n} \geq 0, \quad \frac{dD_n}{d\tau_u} \lessgtr 0$$
$$\frac{dD_u}{d\tau_n} \lessgtr 0, \quad \frac{dD_u}{d\tau_u} \geq 0.$$

Proof: see Appendix B.1.

Proposition 1 has 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 the product of the scrap response and new-used substitution $g'D_c'$ is small, then the supply increase dominates, increasing quantities. But if $g'D_c'$ is large, then the demand decrease dominates, decreasing quantities.

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 $g'D_c'$ is small, then the outward shift dominates, increasing new EV prices and quantities. But if $g'D_c'$ is large, then the inward shift dominates, decreasing prices and quantities.

3.2.2 Rental Price Effects

Proposition 2 presents comparative statics on steady-state rental prices.

Proposition 2. *The steady-state equilibrium rental price effects are*

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

Proof: see Appendix B.2.

The expressions deflate the new subsidy effects by $(1-g)$ because only $(1-g)$ as many consumers receive used subsidies compared to new subsidies, thereby decreasing their effect. This adjustment is equivalent to comparing the two subsidies per dollar of government expenditure (when $g' = 0$). Proposition 2 has two implications. First, both new and used EV subsidies weakly reduce the average rental prices for both ages. Thus, the subsidies directly benefit statutory recipients and also indirectly benefit all buyers of the other age. Second, however, the rental price decreases per dollar of subsidy expenditure are larger for subsidies to the corresponding age than subsidies to the other age. Thus, each subsidy has a kind of "flypaper effect," where the economic benefits stick with the statutory recipients.

So far, we have focused on the ways in which new and used EV subsidies are different. Proposition 3, however, states that if scrappage is perfectly inelastic, then the two subsidies have equivalent effects on rents, and thus equilibrium quantities.

Proposition 3. *If scrappage is fully inelastic ($g' = 0$), then the scrap-rate adjusted steady-state equilibrium 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.3.

Proposition 3 flows from the standard result that economic incidence is independent of statutory incidence. New EV subsidies have statutory incidence on used EV sellers, while used EV subsidies have statutory incidence on used EV buyers (but not scrappers). If the scrap rate is endogenous, we have the "flypaper effects" described above. But if the scrap rate is exogenous, subsidizing sellers versus buyers has the same economic effect.

3.3 Welfare and Optimal Policy

We now consider welfare and optimal policy. For this subsection, we no longer maintain the earlier assumption that all consumer types i have identical demand functions. Instead, we assume that while they have identical demand slopes, higher-income types have stronger preferences for new vehicles. Letting higher i indicate higher income, $i' > i \implies D_{i'n}/D_{i'u} > D_{in}/D_{iu}$.

Welfare is the sum of consumer surplus, new vehicle producer surplus, and negative externality reductions, net of government spending. The government applies welfare weights ω_i to type i's consumer surplus, with average $\bar{\omega}_i = 1$. Higher-income types receive weakly lower weight: $i' > i \implies w_{i'} \leq w_i$. Thus, the welfare function places higher weight on consumers who buy used EVs.

3.3.1 Optimal Subsidies with Full Eligibility

Proposition 4 presents the welfare-maximizing subsidy levels when all consumer types are eligible. Let $b_n \coloneqq Cov(w_i, D_{in})$ and $b_u \coloneqq Cov(w_i, D_{iu})$ represent the covariances of the welfare weights and EV demand.

Proposition 4. *The total surplus-maximizing subsidies are*

$$\begin{aligned} \tau_n^* &= \phi_n + \phi + (p_n - c) + f_n\left(\frac{-dr_n}{d\tau_u}, \frac{-dr_u}{d\tau_n}, \frac{-dr_n}{d\tau_n}, \frac{-dr_u}{d\tau_u}\middle| b_n, b_u\right), \\ \tau_u^* &= \phi + f_u\left(\frac{-dr_n}{d\tau_n}, \frac{-dr_u}{d\tau_u}, \frac{-dr_n}{d\tau_u}, \frac{-dr_u}{d\tau_n}\middle| b_n, b_u\right), \end{aligned} \tag{2}$$

where $f_n', f_u' \geq 0$ in their first two argument and $f_n', f_u' \leq 0$ in the last two arguments.

Proof: see Appendix B.5.

As in Diamond (1975), Allcott, Lockwood, and Taubinsky (2019a), and others, there are two reasons to subsidize EVs: the redistributive motive (the covariance terms) and the corrective motive (all other terms).

To interpret the Proposition 4, first consider the case with equal welfare weights, so $Cov(w_i, D_{in}) = 0 = Cov(w_i, D_{iu})$ and there is only a corrective motive. This delivers the standard Pigouvian result that the total surplus-maximizing policy involves full eligibility and corrective subsidies in each period of the vehicle's life. The corrective subsidies account for all three market failures: the production externality, consumption externality, and markup.

Proposition 4 clarifies that the social optimum involves more than just subsidies for new EVs. This is because used EVs also reduce negative externalities. Unless scrappage is perfectly inelastic, used EVs will be scrapped too early unless there is a subsidy to keep them on the road. In a more general model where EVs live for more than two periods and might be resold more than once, the optimal policy could be an annual tax credit for driving an EV, instead of a one-time tax credit for buying a used EV.

If scrappage is perfectly inelastic, however, then the equivalence result from Proposition 3 implies that the government can achieve the same economically efficient allocation through any appropriate linear combination of new and used EV subsidies. For example, one optimal policy would be zero used EV subsidy plus a new EV subsidy equal to the EV's lifetime negative externality reduction plus the markup: $\phi_n + (2 - g) \cdot \phi + (p_n - c)$.

Now consider the case with unequal welfare weights, adding distributional concerns. The full case is ambiguous, because whereas Proposition 2 emphasizes how new vs used subsidies affect the same rent, for the optimal policy we need to look at the total distributive effects for a subsidy type. This necessitates comparing e.g. $\frac{dr_n}{d\tau_n}$ and $\frac{dr_u}{d\tau_n}$. These relative magnitudes are ambiguous within our model. Therefore, the proposition only says that as new subsidies distribute more to used EV buyers (either by lowering used EV rent more or not lowering new EV rent by as much), then the optimal τ_n^* increases and τ_u^* decreases. The opposite effects increase τ_u^* and decrease τ_n^*.

Vehicle rents are composed of three pieces: new prices, used prices, and subsidies. By investigating how new and used subsidies affect each piece, we can further understand the ambiguity in the welfare weighted optimal policy. First, there is the direct effect of subsidizing consumers, this is welfare improving for used subsidies but not for new subsidies. Second, these is the change in new prices ($\frac{dp_n}{d\tau_x}$) that affect profit margins and new rent. For this force, new subsidies are efficient because they raise new prices which marginally transfers money from new buyers to producers (which have a welfare weight of $\bar{w_i} = 1$), whereas used subsidy have the opposite (inefficient) effect. Third, there is the change in used EV prices which acts as transfers between new EV buyers and used EV buyers. Again, new subsidies are preferred because they lower used EV prices, whereas used subsidies increase used prices. In summary, beyond the direct effects, new EV subsidies are preferred to used EV subsidies, even with welfare weights. This motivates our next section on optimal policy with eligibility restrictions.

3.3.2 Marginal Value of Public Funds with Partial Eligibility

We now consider eligibility restrictions and simplify by assuming $|I|= 2$: a high-income and low-income group. In cases with eligibility restrictions, we assume that only the low-income group, which has higher welfare weight, would be eligible. We also assume low-income consumers purchase a higher ratio of used vehicles than high-income consumers. Denote μ_n and μ_u as the share of new and used EV *buyers* that are eligible. Under these simplifications and a few restrictions, we can show a ranked ordering that per dollar of government expenditure G, new EV subsidies restricted to the low-income group are the best, followed by restricted used EV subsidies and finally unrestricted used EV subsidies (which we indicate by $\mu_u = 1$).

Proposition 5. *Suppose $g' = 0$, $\tau_n = \tau_u = 0$, and $\mu_u - \mu_n \leq C \in \mathbb{R}^{>0}$, then in the steady-state*

$$\frac{dW}{d\tau_n}/\frac{dG}{d\tau_n} \;>\; \frac{dW}{d\tau_u}/\frac{dG}{d\tau_u} \;>\; \frac{dW}{d\tau_{u_{|\mu_u=1}}}/\frac{dG}{d\tau_{u_{|\mu_u=1}}}. \tag{3}$$

Proof: see Appendix B.6.

This proposition follows directly from our discussion in the previous section. Beyond the direct effects, the equilibrium price changes induced by offering new subsidies (p_n increases and p_u decreases) are welfare improving. Thus, when we condition eligibility on the low-income consumers, the best policy is new EV subsidies. While $g' = 0$ and $\mu_n = \mu_u$ imply the new price effects of new and used subsidies are actually identical per dollar of expenditure, these assumptions are stricter than required so relaxing slightly implies the direction of new price changes remains a key force.

The preference to restricted, as opposed to unrestricted, used EV subsidies is less surprising because the equilibrium effects will be similar, just scaled by the amount of government spending. Therefore, restricting the subsidy to low-income consumers will reduce inefficient direct subsidies to high-income consumers, making eligibility restrictions optimal for used EV subsidies as well.

As a note on the proposition's assumptions, we rely on perfectly inelastic scrappage as a simple regularity condition that guarantees pass-through rates are unambiguous and demand derivatives are positive and similar across new and used subsidies, but this condition is stronger than needed. We ignore infra-marginal effects and endogenous μ_n and μ_u by starting from zero subsidies. The C parameter limits the amount of market segmentation by ensuring that at least some of the new market buyers are eligible. It functions similar to $g' = 0$ by regulating pass-through rates.[9]

[9]To see why this is needed, consider the case of perfect segmentation where no new vehicle buyers are eligible. Increasing τ_n will decrease used vehicle demand among eligible used vehicle buyers, depressing used vehicle prices and increasing scrappage. This will shrink the overall car market and decrease new vehicle prices, implying $dp_n/d\tau_n < 0$. We exclude cases such as this by bounding C.

3.4 Comments

Two types of inattention could affect this section's predictions. First, if consumers are inattentive to the 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. 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 $\tilde{v}_{t+1}$ on new vehicle demand.

This theory helps clarify some expected effects of new versus used EV subsidies, but it leaves two questions unresolved. First, since equilibrium price adjustments are central to the theory, how much do used EV subsidies actually affect prices? Second, what are the quantitative effects of EV tax credits 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" ("EVs") to include plug-in hybrids, and we define "gasoline vehicles" ("GVs") 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 and merging the data, 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.

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 (d) present data from the National Household Travel Survey (NHTS).

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 44 and 39 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 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. 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 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: Incidence of Used EV Tax Credit

As described in Section 2, the IRA used EV tax credit began in January 2023 and was available for transactions priced $25,000 or less. Dealership transfer began in January 2024, and the tax credit ended on September 30, 2025. This section describes bunching-based estimates of the short-run effects of the used EV tax credit on EV prices. Appendix D.1 presents difference-in-differences estimates, which are generally less precise.

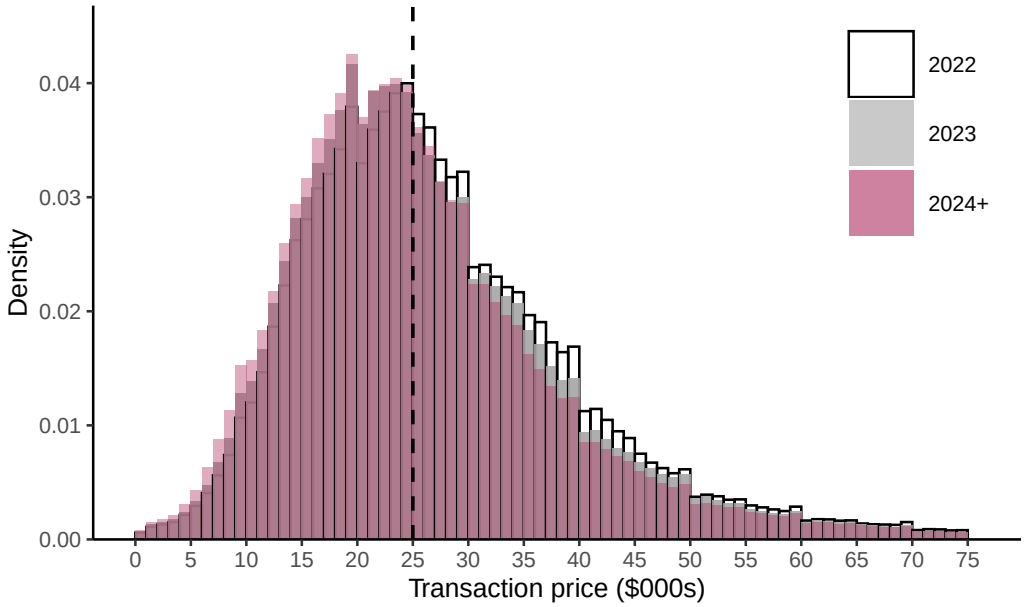
5.1 Descriptive Figures

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 "2024+." Each bar is a bin from $[x],001 to $[x+1],000.

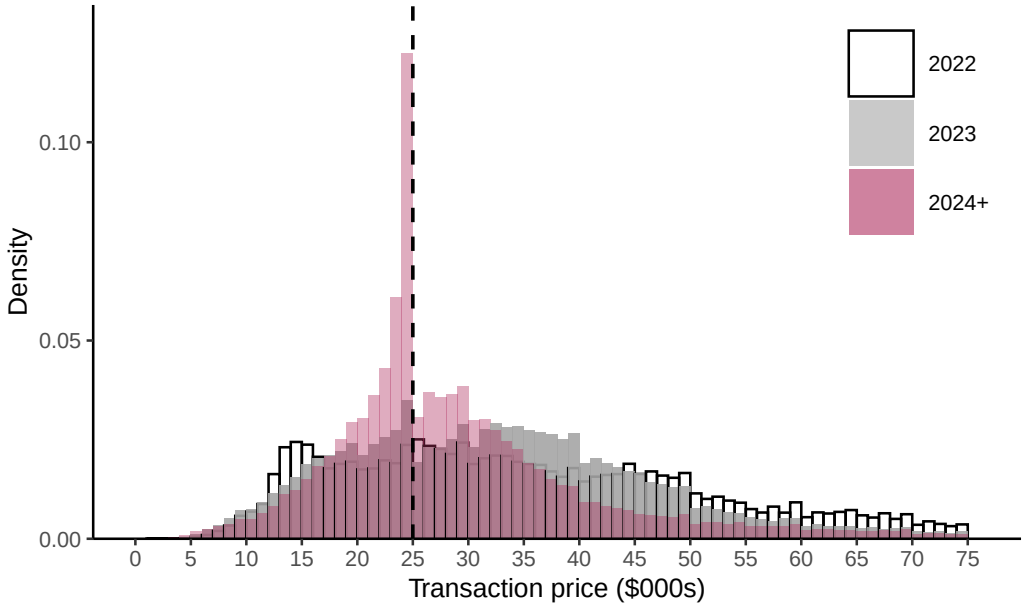
Panel (a) shows that the gas vehicle price distributions for all years are fairly smooth except for "left-digit effects": bunching just below round numbers that are multiples of $5,000 and $10,000. Panel (b) presents

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 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.

the electric vehicle price distributions. Left-digit effects are again clearly visible. In 2022, before the tax credit took effect, there was no visible 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, 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 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 with "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 data. Define $p^L_{iT} \sim L_T$ as the "latent" price—that is, 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 the density is well-approximated by an order-K polynomial:

$$l_0(p) = \sum_{k=0}^{K} \beta_k p^k. \tag{4}$$

We model that the tax credit affects latent prices in ways suggested by the descriptive histograms above. Define $p^* =$ $25,000 as the credit's transaction price limit, $\underline{p}$ as the bottom of the "bunching region," $\overline{p}$ as the top of the "downward bunching" region, and ρ as a pass-through rate formalized below. For our primary analyses, we set $\underline{p} =$ $23,001, meaning that excess mass can arise anywhere in a bunching region from

$23,001 to $25,000, and $\overline{p}$ = $26,000, meaning that downward bunching could occur for transactions that would be priced from $25,001 to $26,000.

We model how tax credits τ_u affect latent prices as follows. Latent prices p_0^L below $\underline{p} - \rho\tau_u$ shift up by a constant amount $\rho\tau_u$. Latent prices p_0^L between $\underline{p} - \rho\tau_u$ and p^* bunch somewhere in the bunching region between $\underline{p}$ and p^*. Latent prices p_0^L between p^* and $\overline{p}$ bunch downward to the bunching region with probability d, and are unaffected with probability $1-d$. Latent prices above $\overline{p}$ are unaffected. Formally, this is

$$\begin{aligned} p_0^L < \underline{p} - \rho\tau_u &\implies p_1^L = p_0^L + \rho\tau_u \\ \underline{p} - \rho\tau_u \le p_L^0 \le p^* &\implies \underline{p} \le p_1^L \le p^* \\ p^* < p_L^0 < \overline{p} &\implies \underline{p} \le p_1^L \le p^* \text{ with probability } d,\ p_1^L = p_0^L \text{ with probability } 1-d \\ \overline{p} \le p_0^L &\implies p_1^L = p_0^L. \end{aligned} \tag{5}$$

These assumptions imply that prices above $\overline{p}$ are unaffected, and prices below $\underline{p}$ have shifted up by a constant amount $\rho\tau_u$. Thus, 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 $\overline{p}$:

$$L_1(\overline{p}) - L_1(\underline{p}) = L_0(\overline{p}) - L_0(\underline{p} - \rho\tau_u). \tag{6}$$

We call this "mass equivalence."

5.3 Bunching Empirical Strategy

Our goal is to estimate f_0, the equilibrium prices without EV tax credits. To translate between l_T and f_T, we estimate the left digit function Λ. To translate from l_1 to l_0, we exploit the intuition that more excess mass implies a larger upward price shift $\rho\tau_u$. Our empirical strategy has 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 $f_0 = \Lambda(l_0)$.

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} is the density of the bin with midpoint b.

Appendix D.4.1 presents details on steps 1 and 3. In brief, we estimate that about 2.1 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.

For step 2, we find the value of the upward price shift $\rho\tau_u$ that explains the amount of observed excess mass. More precisely, we search for the $\rho\tau_u$ that satisfies the mass equivalence constraint (per equation (6)) under a smooth latent counterfactual price distribution l_0 (per equation (4)).

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

$$l_{1b} = \sum_{k=1}^{K} \left(\beta_k \left[b - \underbrace{(\rho\tau_u)\mathbb{1}(b \leq p^*)}_{\text{price shift}} \right]^k \right) + \sum_{i \in \mathcal{B}_E} \gamma_i \mathbb{1}(b = i) + \epsilon_b. \tag{7}$$

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 fits the no-subsidy density l_0, not the upward-shifted with-subsidy density l_1.

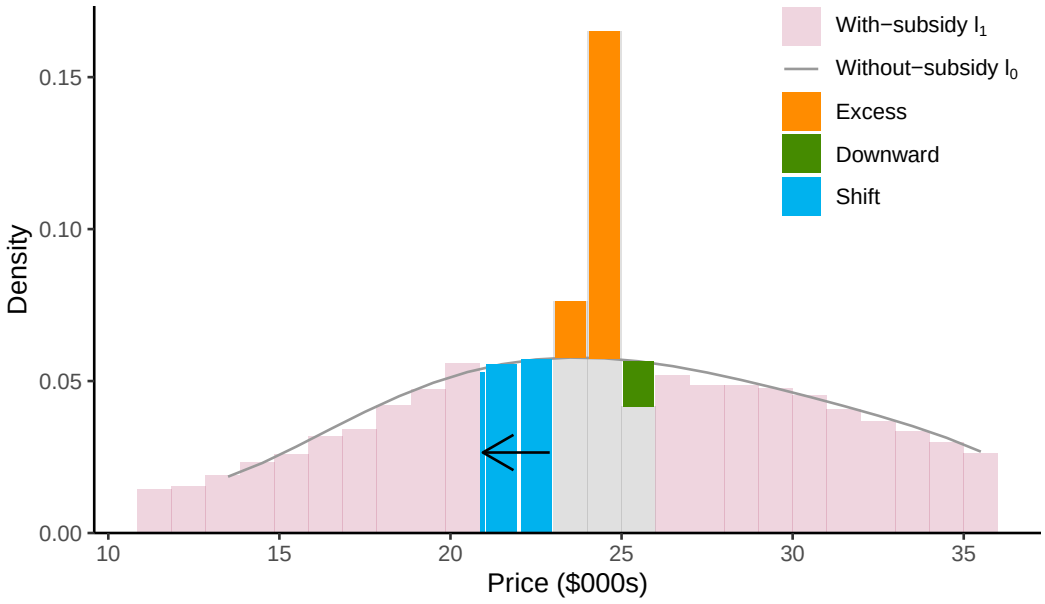
Define $\hat{L}_0(p|\rho\tau_u)$ as the cumulative density implied by evaluating the fitted polynomial $\hat{l}_1$ at the bin midpoints $\mathcal{B}$ and assuming bin uniformity. We search for the $\widehat{\rho\tau_u}$ such that $\hat{L}_0(\bar{p}|\rho\tau_u) - \hat{L}_0(\underline{p} - \rho\tau_u|\rho\tau_u)$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

Figure 2 illustrates the approach, using data from January 2024–September 2025 and our estimated $\widehat{\rho\tau_u} \approx \$2{,}150$. Above \$26,000, the maroon bars are the with-subsidy latent density l_1—i.e., just 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 $\widehat{\rho\tau_u} \approx \$2{,}150$, as illustrated by the black arrow. 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 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.

At the estimated $\rho\tau_u$, the blue counterfactual mass of width $\rho\tau_u$ fits exactly in the orange area net of downward bunching. At a candidate price shift $\rho\tau_u$ that is too small (too large) to satisfy mass equivalence, there is not enough (more) blue mass compared to the orange excess mass net of the green downward bunching. This intuition shows how $\rho\tau_u$ is point identified by our setup.

The above approach is broadly inspired by Kleven and Waseem (2013), but we deviate in two ways. First, our regression in equation (7) 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

Figure 2: **Using Bunching to Identify the Incidence of Used EV Tax Credits**



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

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.

We follow Kleven and Waseem (2013) in using bootstrapped standard errors. Appendix D.4.2 presents details.

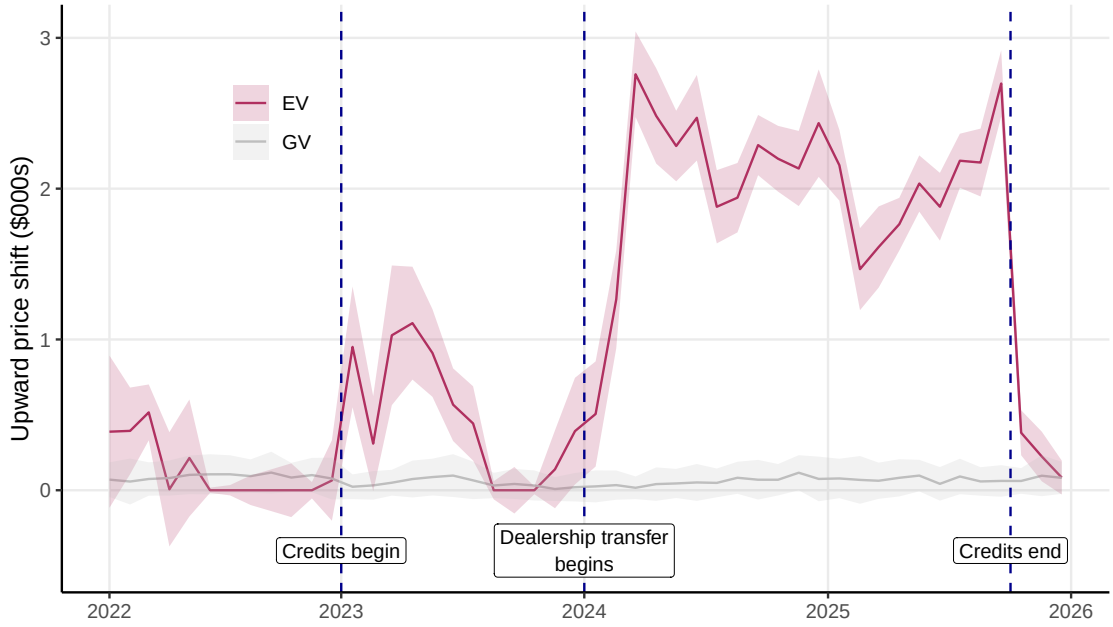
5.4 Bunching Results

Figure 3 presents the estimated upward price shift $\widehat{\rho\tau_u}$ for each month of the sample, separately by powertrain. For gas vehicles, the descriptive histograms in Figure 1 had shown no excess mass of prices below \$25,000. Consistent with that, Figure 3 shows very close to zero price shift for GVs in every month.

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 3 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.[10] The speed of this change suggests that it was caused by a discrete event

[10] 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 the estimates are visually consistent with the monthly price distributions shown in Appendix Figure A11.

Figure 3: **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. The samples limit to used vehicles that were at least two years old, and thus were potentially eligible for the tax credit.

at the beginning of 2024—presumably dealership transfer—instead of more gradual trends 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.

Panel (a) of Table 3 presents formal estimates of $\widehat{\rho\tau_u}$ by period: 2022, 2023, and 2024+. As expected, the GV estimates are small and near statistically 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 begin in 2024.

These estimates do not change substantively in a variety of different alternative specifications presented in Appendix D.4.3, including alternative polynomial orders K and assumptions on the bunching region $\underline{p}$ and downward bunching limit $\overline{p}$.

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 6 in Appendix B.4 reports the theoretically expected upward price shift. In a short-run response to a surprise subsidy, supply of used EVs is fixed. During this period, used EVs had very 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 $\Delta p_{ut} = \mu\tau_{ut}$, where μ is the share of buyers that are eligible for the credit.

In Appendix D.5, we use NVES and IRS data to predict the share of buyers of vehicles costing under $25,000 who have income below the Section 25E limits, and in 2023 also have tax liability. This gives $\mu = 0.49$ for 2023, and $\mu = 0.80$ for 2024, and thus predicted price shifts of $1,970 in 2023 and $3,210 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 more than predicted—somewhat more than predicted in dollar units, and substantially more than predicted in percent terms.

There are several possible reasons for the difference between the estimated versus theoretical upward price shift. First, our arguments above could be imperfect: the theoretical assumptions (e.g., fully inelastic scrappage) may not hold, or our calculation of share eligible μ could be wrong. Second, dealership transfer could have made 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.

Under the price shift assumptions described in equation (5), the estimated upward price shift $\widehat{\rho\tau_u}$ applies directly to eligible EVs with observed prices between $13,333 and $23,000. However, under those same assumptions, we can simulate the full no-subsidy counterfactual price distribution and simulate the price effects in different regions. This is interesting because it allows us to calculate the overall market-wide average price effect, including the *decrease* in prices just above the $25,000 price limit.

Panel (b) of Table 3 presents estimates of the average price effects for vehicles in five different regions of the observed price distribution F_1 for 2023 and 2024+. For observed transaction prices from $0 to $13,333, the used EV tax credit is 30 percent of the price, so the expected price shift is $\hat{\rho} \cdot (0.3p_1)$. The average price increase over the observed transaction prices in 2024+ is $1,610. For observed transaction prices from $13,334 to $23,000, the used EV tax credit is $4,000, so the price shift is $\hat{\rho} \cdot \$4000 \approx \$2{,}157$. Observed transaction prices between $23,000 and $26,000 combine an upward shift averaging $1,453 for transactions that otherwise would have been below $25,000, and downward bunching averaging $314 for transactions that would have been between $25,001 and $26,000. Appendix D.4.4 presents details. Finally, prices above $26,000 were unaffected by assumption. Overall across all sales of used EVs at least two years old between January 2024 and September 2025, the used EV tax credit increased prices by an average of $801.

6 Structural Model

This section presents the structural model. This builds on the theoretical model in Section 3, but enriches the choice set, imposes functional forms, and uses realistic empirical parameters. The upcoming subsections describe the setup, demand, new vehicle supply, used vehicle market, equilibrium simulation, and externality

Table 3: **Estimated Price Effects**

	Panel (a): Upward Price Shift		
	(1)	(2)	(3)
	2022	2023	2024+
GV	109	69	83
	(50)	(44)	(48)
EV	122	406	2,154
	(83)	(80)	(103)
EV (theoretical prediction)	0	1,966	3,214

	Panel (b): Distribution Price Effects			
	2023		2024+	
Observed price range ($000s)	Share of transactions	Average price effect ($000s)	Share of transactions	Average price effect ($000s)
[0, 13.3]	0.049	0.321	0.036	1.610
(13.3, 23]	0.202	0.406	0.233	2.157
(23,26]	0.078	0.313	0.215	1.119
Upward shift	0.056	0.529	0.174	1.453
Downward bunching	0.022	-0.221	0.041	-0.314
26+	0.671	0.000	0.516	0.000
Total	1.000	0.122	1.000	0.801

Notes: Panel (a) shows estimates of $\widehat{\rho\tau_u}$ obtained via jointly estimating equation (7) and finding the $\widehat{\rho\tau_u}$ to solve the excess mass equation. The theoretical row uses our short-run theory prediction that $\Delta p_u = \mu\tau_u$, where μ is our estimate of the share of eligible consumers based on IRS income tax data and vehicle buyer income. Panel (b) shows the transaction share and estimated price effects for different parts of the EV price distribution by year. We describe the methodology in Appendix D.4.4.

calculation.

Two goals were important to our modeling decisions. First, some of the theoretical insights are clearest in a steady-state model, but the actual vehicle market is not in steady state due to policy changes and new EV models. Thus, we want to solve for both steady state 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 steady state, and some other models assume that all

cars are resold each year (e.g., Bento et al. 2009; Jacobsen 2013; Jacobsen and Benthem 2015).

6.1 Setup

Extending our earlier notation, j indexes "car types" (aggregates by brand, powertrain, and class), and a, y, and t index ages, model years, and simulation years, respectively. In any given simulation year, age and model year are co-determined: $t \equiv y + a$. Thus, we will freely switch between a and y in subscripts.

We let $i = \{1, ..., N\}$ index individual consumers and define e_i as an indicator for whether consumer i is eligible for the credit. For both the demand estimation and counterfactual simulations with income limits, we simplify the IRA rules by assuming that consumers are eligible for both the new and used EV tax credits if and only if their household income is less than $150,000 per year.

Within each car type j, the choice set of vehicles available for purchase can include each integer age $a \in \{0, 1, 2, ..., 19\}$. There is no outside option, so all N consumers in the market in year t buy some new or used car.

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 calibrate the scrap elasticity to -0.7, following the empirical estimate from Jacobsen and Benthem (2015). We then estimate the scrap rate 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. See Appendix E.1 for details.

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.

6.2 Demand

We begin with a fairly standard logit model with random coefficients but then extend the model 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

$$U_{ijyt} = \alpha_i^p \underbrace{\left(p_{jyt} + e_i \cdot (p^e_{jyt} - \tau_{jyt}) - \tilde{v}_{jy,t+H_i}\right)}_{\text{net-of-subsidy rent}} + \sum_{h=0}^{H_i-1} \underbrace{\left(\boldsymbol{\alpha}_i^X \boldsymbol{X}_{j,a+h} + \delta_{jy} + \varepsilon_{ijat}\right)}_{\text{annual non-price utility}}. \tag{8}$$

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 $\mu_\epsilon = 5$.[11] 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

$$Pr_{ijyt} = \underbrace{\frac{\exp(V_{ijyt} \cdot \mu_\epsilon)}{\sum_k \exp(V_{ijkt} \cdot \mu_\epsilon)}}_{\text{age choice probability, within model}} \times \underbrace{\frac{\exp(L_{ijt})}{\sum_j \exp(L_{ijt})}}_{\text{model choice probability}}. \tag{9}$$

Define $\boldsymbol{p}_t$ and $\boldsymbol{p}^e_t$ 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: $D_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) = \sum_i Pr_{ijyt}$. Demand among consumers with holding period h is $D^h_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) := \sum_i \mathbb{1}(H_i = h) \cdot Pr_{ijyt}$. Total demand among eligible consumers is $D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) := \sum_i e_i \cdot Pr_{ijyt}$.

6.2.1 Demand Estimation

We assume exogenous parameters and then estimate consumer preferences using an approach broadly analogous to Berry, Levinsohn, and Pakes (2004).

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. See Appendix E.2.1 for details.

[11] Appendix Table A14 shows that alternative values do not substantially affect the estimates.

- **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. See Appendix E.2.2 for 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 71 percent of consumers have household income below $150,000 per year and are thus assumed to be eligible for the tax credits.

- **Tax credit amounts**. We construct the tax credit amounts τ_{jyt} consistent with IRA rules as of January 2023.

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 $\boldsymbol{X}_{j,a+h} := \{EV_j, \mathbb{1}(a+h=0), (a+h)\}$. 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 $\boldsymbol{\nu}_i$:

$$\boldsymbol{\alpha}_i^X = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_{inc}\mathbb{1}(inc_i > \$150k) + \boldsymbol{\sigma}\boldsymbol{\nu}_i. \tag{10}$$

We assume that the three random coefficients are independent. 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 $\boldsymbol{\Theta} := \{\alpha_0^p, \alpha_0^{new}, \alpha_0^{age}, \alpha_{inc}^{EV}, \alpha_{inc}^{new}, \alpha_{inc}^{age}, \sigma^{EV}, \sigma^{new}, \sigma^{age}\}$ as a vector of nine parameters, and define $\boldsymbol{M}(\Theta)$ as a vector of nine 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 nine parameters. The identification is intuitive; we present Andrews, Gentzkow, and Shapiro (2017) sensitivity matrices in Appendix Tables A12 and A13. We use four types of moment conditions.

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**. Three final moments match the covariance of the three vehicle characteristics $\boldsymbol{X}$ across different choices made by the same household. Using NVES data, we construct the share of EV buyers whose second choice was an EV. Using two-vehicle households in the 2009 NHTS (which unlike the 2022 survey, has purchase date for all vehicles), we construct the share of new vehicle buyers whose other vehicle was bought new, as well as the correlation between the two vehicles' ages at purchase. The random coefficient dispersions $\boldsymbol{\sigma}$ are particularly sensitive to these moments.

Appendix E.2.3 presents formal details on the estimator and moment conditions as well as tables of the empirical moments and parameter estimates.

Table 4 summarizes the demand estimation results by presenting key elasticities implied by the estimates. The average own-price elasticity for new car types is -4.84, somewhat more than the average firm-level elasticity of -4.57, which was targeted in the estimation. The aggregate new vehicle price elasticity is -1.46, which is fairly close to the estimate of -1.29 in Grieco, Murry, and Yurukoglu (2024). The aggregate price elasticity of demand for new EVs is -0.45, 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 suggest that the EV powertrain preference is stronger than the age preference: for new EVs, there is more diversion to used EVs than to new GVs, and for used EVs, there is much more diversion to new EVs than to used GVs. The bottom two rows show that the pure characteristics model

delivers substantial substitutability between ages of the same car type. In particular, when the price of the average age 7 car type rises, 75 percent of the diversion is to other ages of that same car type.

Table 4: **Selected Elasticities**

Parameter	Estimate
Average new car type price elasticity	-4.84
Average firm-level price elasticity (Ford, GM, Toyota, Volkswagen, Hyundai)	-4.57
Aggregate new vehicle price elasticity	-1.46
Aggregate new EV price elasticity	-1.20
Aggregate (new+old) EV price elasticity	-0.45
New EV $\rightarrow$ new GV diversion ratio	0.36
New EV $\rightarrow$ used EV diversion ratio	0.42
Used EV $\rightarrow$ used GV diversion ratio	0.14
Used EV $\rightarrow$ new EV diversion ratio	0.42
New car type $\rightarrow$ used ages average diversion ratio	0.18
Age 7 car type $\rightarrow$ other used ages average diversion ratio	0.75

Notes: This table presents key elasticities implied by our demand estimates. When taking averages across car types and ages, we weight by market shares.

6.3 New Vehicle Supply

New vehicles are supplied in static Nash-Bertrand competition, exactly analogous to Berry, Levinson, and Pakes (1995) and subsequent work. 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) and c_j do not change across years, staying fixed at their 2023 values. Firm f's profit function is the sum of profits over vehicles they make ($j \in \mathcal{J}_f$) of the current model year ($y = t$):

$$\pi_{ft} = \sum_{j \in \mathcal{J}_f, y=t} (p_{jyt} - c_j) \cdot D_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}_t^e). \tag{11}$$

As in Berry, Levinsohn, and Pakes (1995) and most other work, this assumes that firms do not consider dynamic incentives, i.e. that new vehicle sales in one year affect demand and profits in future years. To the extent that firms did consider such factors in when setting observed prices, this will be included in our estimates of marginal opportunity cost c_j, which we assume is unchanged across counterfactuals. Separately, we assume that firms set prices assuming D_{jyt} such that if a new vehicle's price changes by x percent, its expected resale value $\tilde{v}_{jy,t+H_i}$ also changes by x percent. This is an implicit assumption made in Berry,

Levinsohn, and Pakes (1995) and other papers studying only new vehicle markets, but we must make it explicit because our demand functions depend on resale values, not just new vehicle prices.

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 \$10,300, or 23 percent of the price. Appendix Figure A17 presents the distribution of implied markups across vehicles.

6.4 Used Vehicle Market Clearing

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.

Rental car companies and motor pools typically buy new vehicles and eventually resell them to individual consumers. If we do not account for these fleet sales, our model has excess demand for young used vehicles, and thus unrealistically high prices. Appendix E.4 describes how we construct fleet sales S_{jat}^{fleet} from the Experian data. We assume that S_{jat}^{fleet} is exogenous. We also assume that these are all first transfers and thus are potentially eligible for used EV tax credits.

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

$$D_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}_t^e) = S_{jat}^{fleet} + (1 - g_{ja}(p_{jyt})) \cdot \sum_{h=1}^{19} D_{jy,t-h}^{h}. \tag{12}$$

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.5 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 more than 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:

$$S_{jyt}^{e}(p_{jyt} + p_{jyt}^{e}) = S_{jat}^{fleet} + (1 - g_{ja}(p_{jyt} + p_{jyt}^{e})) \cdot \sum_{h=\min(t-2023, t-y)}^{t-y} D_{jy,t-h}^{h} \tag{13}$$

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 must always be 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 $p^e_{jyt} = \tau_{jyt}$; (ii) supply equals demand for eligible VINs, with $0 \leq p^e_{jyt} \leq \tau_{jyt}$; and (iii) excess supply of eligible VINs, with $p^e_{jyt} = 0$. Considering thee three possibilities, the eligible VIN market-clearing condition within each eligible ja is

$$\begin{aligned}
&\textit{Excess demand, max eligibility premium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) > S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies p^e_{jyt} = \tau_{jyt} \\
&\textit{Interior equilibrium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) = S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies 0 \leq p^e_{jyt} \leq \tau_{jyt} \\
&\textit{Excess supply, zero eligibility premium:} && D^e_{jyt}(\boldsymbol{p}_t, \boldsymbol{p}^e_t) < S^e_{jyt}(p_{jyt} + p^e_{jyt}) \implies p^e_{jyt} = 0.
\end{aligned} \tag{14}$$

6.5 Equilibrium Simulation

Summarizing the above, an equilibrium is a vector of prices and eligibility premia $\{\boldsymbol{p}_t, \boldsymbol{p}^e_t\}$ for all years t such that

1. scrap quantities are consistent with prices, per equation (104) in Appendix E.1;
2. consumers' choices maximize utility from equation (8);
3. consumers correctly forecast vehicle prices: $\tilde{\boldsymbol{p}}_t = \boldsymbol{p}_t, \tilde{\boldsymbol{p}^e_t} = \boldsymbol{p}^e_t, \forall t$;
4. firms maximize profits from equation (11);
5. used vehicle markets clear, following equation (12); and
6. markets for eligible VINs clear, following equation (14).

We find steady-state equilibria by iterating over beliefs, prices, and demand until convergence. For the non-stationary equilibria, we assume that starting in 2043, consumers believe that vehicle prices $\boldsymbol{p}_t$ will take their steady state values with no tax credits. We then forward simulate over the 20 years from 2023 to 2042, again iterating over beliefs, prices, and demand until convergence. Appendix E.6 provides details, and Appendix E.7 describes the surplus calculations.

6.6 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) fiscal externalities from gasoline taxes and

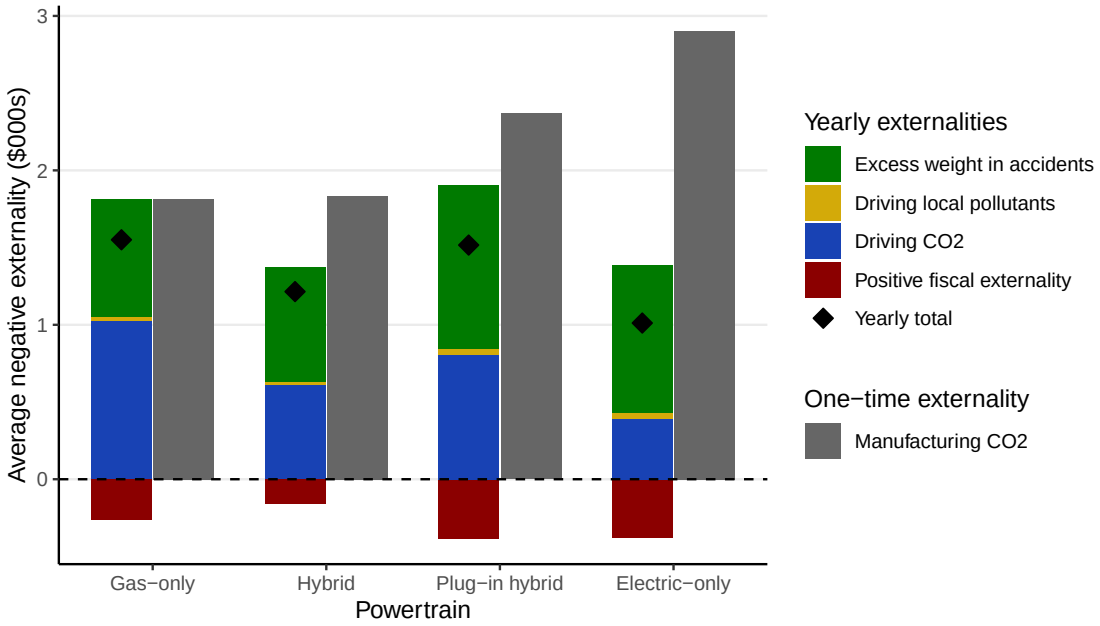
residential electricity markups. We measure externalities by car type and model year, generally following Allcott et al. (2024). Appendix E.8 provides details.

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 constant mileage by age so that total mileage stays the same when consumers substitute between newer and older vehicles in counterfactual simulations.

Figure 4 presents average externalities by powertrain. EVs (averaging over electric-only and plug-in hybrids) have higher manufacturing CO_2 externalities than GVs (averaging over gas-only and hybrids): $2,810 versus $1,820. EVs also have higher accident externalities, because they weigh more. However, their driving CO2 emissions are lower, and their positive fiscal externality is higher due to residential electricity price markups. In total, EVs impose $1,100 in yearly externalities, against $1,520 per year from GVs.

Our scrap rates imply an average vehicle lifetime of 16.3 years. Summing manufacturing and driving externalities over that lifetime, EVs and GVs impose total negative externalities of about $20,800 and $26,700, respectively. In the simple model from Section 3, with zero markups, inelastic scrappage, and equal welfare weights across consumers, the Pigouvian optimum would be to subsidize new EVs by $26,700 – $20,800 ≈ $5,900. However, externalities vary substantially across models (see Appendix Figure A19), so heterogeneous vehicle-specific taxes would be more economically efficient.

Figure 4: **Average Externality by Powertrain**



Notes: This figure presents average externalities by powertrain for new vehicles, weighting car types by 2023 sales.

7 Counterfactual Simulations

We present three sets of counterfactual policy simulations. First, we analyze the steady state effects of new and used EV subsidies, including the price and income limits implemented under the IRA. Second, we use the steady state framework to characterize optimal policy. We examine the optimal combination of new and used EV subsidies and compare it to alternative policy designs, including EV usage subsidies, GV usage taxes, and the first-best policy that directly targets externalities and markups. Finally, we move beyond the steady state and study non-stationary equilibrium. We consider a policy that lasts for ten years, and analyze the resulting transition dynamics over a 19-year horizon. We also simulate a policy that closely matches the IRA design and evaluate its welfare implications

7.1 Steady State Equilibrium

Table 5 presents market outcomes and welfare effects of new and used EV subsidies under various eligibility rules based on price and income. Column 1 presents the no-subsidy equilibrium results, while columns 2–4 show results for a $4,000 new EV subsidy with no limits, income limits ($150,000), and combined income plus price limits ($50,000), respectively. Columns 5–7 show the results for an equivalent set of policies with a $4,000 used EV subsidy. Panel (a) presents EV-related equilibrium outcomes, while Panel (b) presents welfare changes, in billions of dollars, for each policy scenario relative to the no-subsidy baseline.

In Panel (a), both new and used EV subsidies increase EV sales and registrations, but new EV subsidies are more effective at increasing the EV share for the same subsidy level. Adding eligibility requirements generally attenuates these effects by limiting both the direct and equilibrium impacts of the subsidies. Turning to prices, a new EV subsidy increases the gap between new and used EV prices–which is closely related to new EV rents–by about $1,000. This increase is smaller than the $4,000 subsidy, implying that eligible new EV buyers benefit from the policy. In contrast, a used EV subsidy raises used EV prices by roughly $2–3,000, also less than $4,000, so eligible used EV buyers benefit as well. Consistent with the theoretical framework, both policies generate cross-consumer benefits through vehicle stock accumulation and resale value adjustments. In particular, a new EV subsidy increases EV stock accumulation and reduces used EV prices by approximately $2–3,000, benefiting used EV buyers. Conversely, a used EV subsidy raises used EV prices (resale values), thereby benefiting new EV buyers. The reduction in the new-used price gap with used EV subsidies reflects the reduction in new EV rents.

Panel (b) presents welfare changes relative to the no-subsidy baseline. Both new and used EV subsidies increase consumer surplus, although the magnitude of the gains declines as eligibility conditions are introduced. Across all specifications, the increase in consumer surplus is larger for low-income households than for high-income households. Moreover, introducing income and price eligibility conditions generally

Table 5: **Effects of EV Subsidies in Steady-State Equilibrium**

	(1) No subsidy	(2) New subsidy	(3) New subsidy + income limit	(4) New subsidy + inc & price limit	(5) Used subsidy	(6) Used subsidy + income limit	(7) Used subsidy + inc & price limit
Panel (a): Market Statistics							
EV registrations share (%)	9.24	10.35	10.25	9.99	9.50	9.55	9.33
New EV sales share (%)	9.95	11.70	11.57	11.24	10.27	10.38	10.02
New EV avg price ($000s)	52.08	50.22	49.92	50.43	54.03	53.67	52.87
Used EV avg price ($000s)	24.27	21.17	21.37	22.19	27.37	27.17	26.50
New - used EV price ($000s)	27.81	29.05	28.55	28.24	26.66	26.5	26.37
Panel (b): Welfare Relative to No Subsidy (Billions)							
ΔCS	-	5.49	4.62	3.50	1.39	1.62	0.56
ΔCS with inc $\leq$ \$150k	-	4.09	4.18	3.17	1.02	1.29	0.39
ΔCS with inc $\geq$ \$150k	-	1.40	0.44	0.33	0.37	0.34	0.17
ΔCS with inc $\geq$ \$150k / ΔCS	-	0.25	0.10	0.09	0.26	0.21	0.30
ΔProfit	-	-1.07	-1.26	-0.97	1.85	1.60	0.71
ΔGV profit	-	-0.90	-0.68	-0.53	-0.20	-0.26	-0.05
ΔEV profit	-	-0.16	-0.58	-0.44	2.05	1.85	0.76
ΔNegative externality	-	-0.42	-0.39	-0.45	-0.12	-0.14	-0.07
ΔGV externality	-	-2.52	-2.31	-1.76	-0.62	-0.76	-0.22
ΔEV externality	-	2.10	1.92	1.31	0.51	0.62	0.15
Gov't expenditure	-	4.04	3.21	2.48	3.38	3.34	1.23
ΔCS + Δprofit - Δexternality - ΔGov't	-	0.80	0.54	0.50	-0.03	0.02	0.10
MVPF	-	1.20	1.17	1.20	0.99	1.01	1.08
Pareto-weighted MVPF	-	1.17	1.34	1.38	0.98	1.02	1.05

Notes: Each column shows the outcomes in steady state for a given policy. New and used subsidies are each \$4,000, income limits are \$150,000, and price limits are \$50,000 for new EVs and \$25,000 for used EVs. We calculate pareto welfare weights as 1/income and then normalize so the average weight is 1.

reduces the share of consumer surplus change of high-income consumers in total consumer surplus change. This suggests that the distributional effects shift toward the intended direction.

Used EV subsidies increase profits. By raising resale values, used EV subsidies stimulate demand for new EVs, which increases EV producer profits. This increase more than offsets the decline in GV profits, resulting in a net increase in total profits. In contrast, new EV subsidies reduce EV profits, which is counterintuitive. The expansion of EV stock substantially lowers resale values, which in turn reduces new EV prices overall, even though new EV rents increase. This mechanism is amplified by the model structure, which features strong within-model substitution, perfect foresight, and fully patient consumers, causing resale price effects to have a relatively large impact on new vehicle demand.

In terms of externalities, EV subsidies increase the stock of EVs and therefore raise EV-related negative externalities. However, this is more than offset by a reduction in GV externalities as consumers substitute away from gasoline vehicles. As a result, total negative externalities decline. Used EV subsidies gener-

ate relatively small reductions in externalities while requiring substantial fiscal cost, reflecting large inframarginal transfers. By increasing resale prices, they transfer rents broadly rather than primarily inducing marginal adoption. Consistent with this, removing income and price limits from used EV subsidies reduces externalities by only $50 million per year but increases government expenditure by $2.15 billion annually. This suggests that price and income limits improve targeting by reducing transfers to inframarginal buyers.

Finally, in terms of total surplus, EV subsidies generally increase overall welfare but the gains are larger for new EV subsidies than for used EV subsidies. We provide a more detailed explanation for this difference in the next subsection. If we consider an equity perspective, the Pareto-weighted marginal value of public funds (MVPF), using consumer weights proportional to the inverse of income, increases substantially with income limits for new subsidies but only mildly for used subsidies. These findings are consistent with Proposition 5, which says equity goals are more effectively achieved through targeted new EV subsidies than through subsidizing (even targeted) used EV transactions.

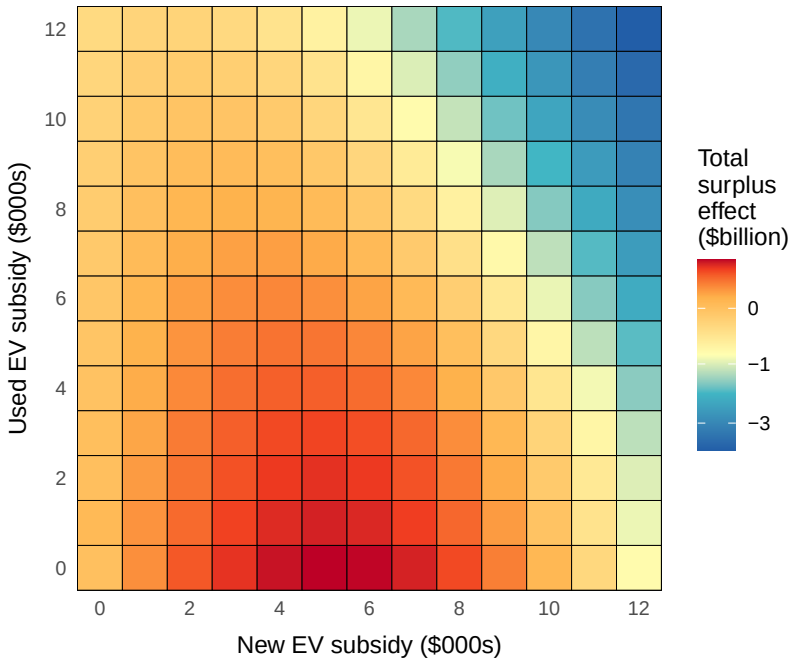
7.2 Optimal Steady State Policy

Figure 5 shows a heatmap of total surplus changes relative to the no-subsidy baseline across a grid of new and used EV subsidies in steady state equilibrium. We find that the optimal policy features a new EV subsidy of approximately $5,000 and no used EV subsidy. At first glance, this result appears to contradict the theoretical model in Section 3, which predicts a nonzero optimal used EV subsidy. In that framework, used EV subsidies improve efficiency by reducing suboptimally early scrappage. In particular, new and used subsidies have opposing effects on scrappage: used subsidies reduce scrappage, while new subsidies increase it.

The key difference is that the theoretical framework abstracts from markups in the GV market. In the presence of GV markups—which introduce an additional distortion—new EV subsidies raise EV scrappage, by increasing EV stock, and generate additional new GV sales. This creates an additional efficiency gain, as these new GV sales yield producer surplus in a high-markup market. In contrast, used EV subsidies reduce scrappage and therefore limit this reallocation toward new GV purchases. As a result, they forgo this additional channel of efficiency gains associated with GV markups. We formalize this mechanism in Appendix B.7. Under mild assumptions, higher average markups (holding the relative markup difference betwen EVs and GVs fixed) reduce the optimal used EV subsidy and increase the optimal new EV subsidy. For empirically relevant levels of markups, this effect is strong enough to overturn the scrappage-based rationale for used EV subsidies, reconciling the steady state results in Figure 5 with the earlier theoretical framework.

Table 6 shows how optimal policies change under alternative policy designs and how total surplus can be further improved. First, we consider alternative age restrictions for used EV subsidies. Under the IRA, used

Figure 5: **Total Surplus Effects of New and Used EV Subsidies**



Notes: This figure shows total surplus changes relative to the no-subsidy baseline across a grid of new and used EV subsidies in steady state equilibrium. Each cell represents the total yearly surplus (in billions of dollars) for a given combination of new and used EV subsidies. Warmer colors indicate higher surplus gains, while cooler colors indicate lower or negative surplus effects.

EV subsidies apply to the first transfer of vehicles aged two or older. As shown in Appendix Figure A20, approximately 75 percent of new vehicle buyers hold their vehicles for less than ten years, implying that most first transfers occur when vehicles are relatively young. At the same time, vehicles under age ten have substantially lower scrap rates than older vehicles. This implies that most vehicles receiving used subsidies under the IRA would not have been scrapped even in the absence of the policy. In our theoretical framework, the primary efficiency rationale for used EV subsidies is to reduce inefficiently early scrappage. Therefore, targeting older vehicles that are closer to the scrappage margin can improve more efficiency.

Columns (2) and (3) compare outcomes under optimal new and used subsidies with age two versus age ten eligibility, respectively. Column (2) corresponds to Figure 5, where the optimal policy is $(\tau_n^*, \tau_u^*) = (\$5{,}000, \$0)$. Figure A21 presents the corresponding heatmap under age ten eligibility, where the optimal policy becomes $(\$5{,}000, \$5{,}000)$. Increasing the minimum eligibility age for used subsidies to ten raises total surplus by approximately $50 million per year. This is because the subsidy is more effectively targeted toward vehicles that are closer to the scrappage margin, allowing it to reduce inefficient scrappage rather than primarily affecting vehicles that would have remained in use anyway.

Next, we relax the requirement that subsidies are provided only at the time of purchase. Under the

Table 6: **Effects of Alternative Policies in Steady-State Equilibrium**

	(1) No subsidy	(2) Optimal transaction subsidy (age 2 limit)	(3) Optimal transaction subsidy (age 10 limit)	(4) Optimal annual EV subsidy	(5) First best (subsidy + GV)
Panel (a): Market Statistics					
EV registrations share (%)	9.24	10.63	10.67	10.63	10.32
New EV sales share (%)	9.95	12.20	12.26	12.20	11.01
New EV avg price ($000s)	52.08	49.83	50.13	49.83	49.40
Used EV avg price ($000s)	24.27	20.45	22.19	20.45	19.27
New - used EV price ($000s)	27.81	29.38	27.94	29.38	30.13
Panel (b): Welfare Relative to No Subsidy (Billions)					
ΔCS	-	6.92	7.43	6.92	-176.50
ΔCS with inc $\leq$ $150k	-	5.17	5.52	5.17	-137.08
ΔCS with inc $\geq$ $150k	-	1.76	1.90	1.76	-39.42
ΔCS with inc $\geq$ $150k / ΔCS	-	0.25	0.26	0.25	0.22
ΔProfit	-	-1.36	-1.16	-1.36	-21.11
ΔGV profit	-	-1.18	-1.36	-1.18	-20.50
ΔEV profit	-	-0.18	0.20	-0.18	-0.61
ΔNegative externality	-	-0.52	-0.57	-0.52	-5.63
ΔGV externality	-	-3.17	-3.35	-3.17	-7.57
ΔEV externality	-	2.65	2.78	2.65	1.94
Gov't expenditure	-	5.25	5.94	5.25	-207.66
ΔCS + Δprofit - Δexternality - ΔGov't	-	0.84	0.89	0.84	15.68
MVPF	-	1.16	1.15	1.16	-
Pareto-weighted MVPF	-	1.13	1.12	1.13	-

Notes: Each column shows the outcomes in steady state for a given policy. For columns two and three we find the optimal combination of new and used transaction subsidies, where the age eligibility is the earliest eligibility for used EV subsidies. Column 4 presents welfare for the optimal one-time new EV subsidy and annual used EV subsidy. Column 5 uses a yearly Pigouvian subsidy accounting for model-specific externalities and markups. We calculate pareto welfare weights as 1/income and then normalize so the average weight is 1.

IRA, subsidies are applied as one-time transaction payments, regardless of how long the vehicle is held. This implies that buyers who hold vehicles for short or long durations receive the same subsidy despite generating different externality reductions. To address this, we simulate an annual EV ownership subsidy over the holding period to target usage-related externalities, combined with a first-year subsidy for new EV purchases to address markups. We find that the optimal ownership policy is functionally equivalent to the age two transaction subsidy: a $5,000 subsidy in the first year and zero thereafter, so the results in Column (4) of Table 6 are identical to those in Column (2). The annual subsidy is offered throughout all holding years, including the early years of the vehicle lifespan. It generates similar inefficiencies related to GV markups as the transaction subsidy with age two eligibility. These inefficiencies dominate any potential

gains from better aligning subsidies with the timing of externality reductions. Consequently, the optimal policy places all weight on new EV subsidies, leading Columns (2) and (4) to deliver the same equilibrium outcomes.

Finally, Column (5) presents the most flexible subsidy and tax structure, achieving the first best. We implement this by providing a subsidy for new vehicle purchases equal to the equilibrium markups and imposing an annual tax equal to the vehicle-specific externality. Note that policies that target only EV adoption deviate from Pigouvian principles in the presence of GV markups as well as variation in externalities. As shown in Appendix Figure A19, variation in externalities within EVs exceeds the average difference between EVs and GVs. Thus, the first-best policy should account for markup distortions, manufacturing externalities, and driving externalities at the vehicle and age level. The implied annual tax revenue is substantial, at nearly $208 billion. This policy increases total surplus by approximately $15.5 billion relative to the no-subsidy baseline and by more than $14 billion compared to the next-best policy.

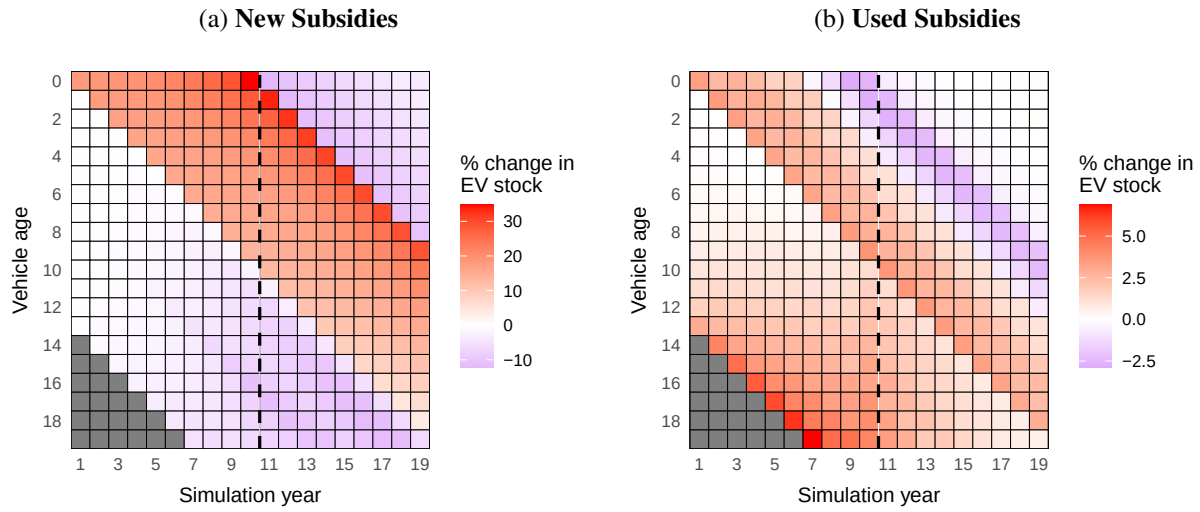
7.3 Non-Stationary Equilibrium

We now move beyond the steady state and examine short-run equilibrium transition dynamics when a temporary policy is introduced and later removed. This setting is particularly relevant in practice, as the IRA EV subsidies were designed to last for a finite period (approximately ten years). To simulate the equilibrium transition path, we introduce a subsidy policy that remains in place only for ten years. Consumers are forward-looking and have perfect foresight, meaning they fully anticipate both the expiration of the policy. Solving for the transition path requires specifying a terminal condition. We assume that by year 20 (i.e., ten years after the policy is removed), prices converge back to the no-subsidy steady state. We therefore fix year-20 prices at their steady-state no-subsidy values and solve backward to obtain the equilibrium price path over the preceding 19 years.

Figure 6 shows the resulting changes in EV stock relative to the no-policy baseline. The left panel presents a $4,000 new EV subsidy (without price or income eligibility restrictions), while the right panel presents a $4,000 used EV subsidy. Each cell reports the percentage change in EV stock by vehicle age and simulation year. One of the key differences between the two policies is their impact on older used vehicles. New EV subsidies increase scrappage of existing used EVs during the policy period, reducing the stock of older used vehicles. In contrast, used EV subsidies reduce scrappage and increase the stock of older used EVs. In terms of overall EV stock accumulation, new EV subsidies are substantially more effective. New EV subsidies increase EV stock by more than 30 percent in some age-year cells, whereas used EV subsidies generate increases of less than 5 percent throughout the transition.

A central distinction lies in the timing of equilibrium effects. New EV subsidies primarily affect future resale markets: a subsidy in period t increases EV adoption today, which raises the supply of used EVs and

Figure 6: **Evolution of EV Stocks**



Notes: This figure shows the percentage change in EV stock relative to the no-policy baseline over the equilibrium transition path. The policy is introduced in year 1 and remains in place for 10 years, after which it is removed. Consumers have perfect foresight about the policy path. The left panel presents a $4,000 new EV subsidy, while the right panel presents a $4,000 used EV subsidy. Each cell corresponds to a vehicle age–year combination and reports the percentage change in EV stock.

affects used EV prices in future periods $t+k$. In contrast, used EV subsidies operate through resale values: a subsidy in period t raises expected resale prices, which feeds back into the demand for new and very young used EVs in earlier periods $t-k$. This difference has important implications for transition dynamics. Under new EV subsidies, the effects on EV stock accumulation persist throughout the policy period and adjust sharply once the policy is removed. By contrast, under used EV subsidies, the positive demand effects on new and younger EVs begin to unwind even before the policy expires, due to the *backward* effect of resale values on earlier purchase decisions. As a result, the transition dynamics under used EV subsidies are more muted and begin to reverse earlier, reflecting the intertemporal nature of resale price expectations.

Table 7 presents results for the full 19-year non-stationary simulation, with panel (b) reporting aggregate welfare effects. Column (1) shows the no-subsidy equilibrium path, Columns (2) and (3) present $4,000 new and used EV subsidies without eligibility limits, and Column (4) approximates the IRA policy with a $7,500 new EV subsidy and $4,000 used EV subsidy, combined with income and price limits.

Consistent with the transition dynamics shown in Figure 6, new EV subsidies have substantially larger effects on equilibrium outcomes than used EV subsidies. This is particularly evident in externalities: new EV subsidies increase EV stock significantly and induce greater substitution from GVs to EVs, reducing total negative externalities by $5.81 billion over the simulation horizon. In contrast, used EV subsidies generate only a modest reduction of $0.70 billion, reflecting their weaker effect on EV adoption.

New EV subsidies generate total surplus gains that exceed government expenditure, yielding a positive

Table 7: **Effects of EV Subsidies on in Non-Stationary Equilibrium**

	(1) No subsidy	(2) New subsidy	(3) Used subsidy	(4) IRA
Panel (a): Market Statistics				
EV registrations share (%)	6.92	7.57	6.98	7.66
New EV sales share (%)	11.86	13.03	11.92	13.32
New EV avg price ($000s)	54.05	53.03	54.67	52.98
Used EV avg price ($000s)	27.08	25.00	28.29	25.50
New - used EV price ($000s)	26.97	28.03	26.38	27.48
Panel (b): Welfare Relative to No Subsidy (Billions)				
ΔCS	-	62.66	14.95	73.61
ΔCS with inc $\leq$ \$150k	-	47.75	11.11	66.50
ΔCS with inc $\geq$ \$150k	-	14.91	3.83	7.12
ΔCS with inc $\geq$ \$150k / ΔCS	-	0.24	0.26	0.10
ΔProfit	-	-8.87	11.67	-11.41
ΔGV profit	-	-9.65	-0.08	-10.15
ΔEV profit	-	0.77	11.75	-1.26
ΔNegative externality	-	-5.81	-0.70	-10.46
ΔGV externality	-	-33.13	-2.89	-37.89
ΔEV externality	-	27.32	2.19	27.43
Gov't expenditure	-	46.19	30.02	69.16
ΔCS + Δprofit - Δexternality - ΔGov't	-	13.40	-2.71	3.50
MVPF	-	1.29	0.91	1.05
Pareto-weighted MVPF	-	1.09	0.97	1.08

Notes: Each column shows the average market statistics and total welfare effects across the 19 years of our non-stationary equilibrium simulations. The new and used subsidies in columns 2 and 3 are both \$4,000 each with no income or price restrictions. The IRA simulation in column 4 simulates \$7,500 new subsidy and \$4,000 used subsidy with \$150,000 income limits and transaction price caps of \$50,000 and \$25,000, respectively. We use Pareto-weights of 1/income and then normalize so the average weight is 1.

net welfare effect and an MVPF of 1.29. By contrast, used EV subsidies generate total surplus that is smaller than government expenditure, leading to a net welfare loss and an MVPF below one. This difference is closely related to the forward and backward benefits discussed earlier. New EV subsidies generate forward effects by expanding future EV stock and benefits future used EV buyers even after the policy expires. In

contrast, used EV subsidies generate backward effects through higher resale values, which increase demand for newer vehicles in earlier periods. When the policy is temporary, these backward effects are truncated, making used EV subsidies less cost-effective.

In addition, the presence of GV markups further amplifies the relative advantage of new EV subsidies. By increasing EV scrappage and inducing substitution toward new GVs, new EV subsidies generate additional reductions in deadweight losses in the GV market. In contrast, used EV subsidies, which reduce scrappage, limit this channel and therefore forgo these additional welfare gains.

Finally, Column (4) shows that the IRA generates positive welfare gains of $3.5 billion over 19 years, although smaller than the $13.4 billion from a uniform new EV subsidy. However, the IRA performs better along distributional dimensions: only 10 percent of consumer surplus gains accrue to households with income above $150,000, and the Pareto-weighted MVPF is comparable to that of the new subsidy. Externality reduction per dollar of government expenditure is also relatively high. These results suggest that while the IRA does not maximize total surplus, its design reflects a trade-off between efficiency and equity, prioritizing distributional objectives.

8 Conclusion

This paper provides a comprehensive evaluation of new versus used EV subsidies, focusing on their efficiency, incidence, and distributional effects in dynamic vehicle markets with resale. While used EV subsidies are often motivated by equity concerns, we show that their economic effects differ from their statutory intent due to equilibrium price adjustments and intertemporal dynamics.

We begin with a theoretical framework in which resale markets shape subsidy incidence. New EV subsidies lower used EV prices and benefit used EV buyers, while used EV subsidies raise resale values and benefit new EV buyers. With inelastic scrappage, these forces imply equivalence between new and used subsidies in steady state. When scrappage is elastic and markets feature markups, however, this equivalence breaks down, and optimal policy depends on both dynamic incentives and market structure. We then provide empirical evidence on short-run incidence using a novel bunching estimator. We find limited price effects in 2023 but substantial effects in 2024, when credits became immediately available at dealerships, highlighting the importance of implementation and salience.

To quantify policy effects, we develop a dynamic structural model with vehicle holding periods, resale markets, and imperfect competition. In steady state, new EV subsidies more effectively increase adoption, reduce externalities, and raise welfare. Targeting new EV subsidies with income limits improves both efficiency and equity, whereas used EV subsidies remain broadly distributed due to resale price adjustments. We further show that GV markups fundamentally alter optimal policy. By increasing EV scrappage and inducing substitution toward new GVs, new EV subsidies reduce deadweight loss in the GV market. Used

EV subsidies, by reducing scrappage, limit this channel and forgo these gains, overturning the standard scrappage-based rationale for used subsidies in empirically relevant settings.

In non-stationary equilibrium, policy timing becomes central. New EV subsidies generate forward effects by increasing current adoption and future EV stock, with benefits that persist after expiration. Used EV subsidies generate backward effects through resale value expectations, affecting earlier purchase decisions. When policies are temporary, these backward effects are truncated, reducing their effectiveness. As a result, new EV subsidies deliver larger welfare gains and higher MVPFs. Finally, we evaluate the IRA. While it does not maximize total surplus relative to simpler new EV subsidies, it performs well on distributional grounds. Income and price limits effectively target lower-income consumers, reflecting a trade-off between efficiency and equity. More broadly, equity goals are better achieved through targeted new EV subsidies than through subsidizing used EV transactions.

Overall, our findings highlight three lessons. First, equilibrium price adjustments reshape subsidy incidence in resale markets. Second, dynamic considerations—especially forward versus backward effects—are central to policy effectiveness. Third, with market power and heterogeneous externalities, optimal policy must jointly address adoption, resale markets, and markup distortions. These insights extend to other durable goods markets with active secondary markets.

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Online Appendix

The Economics of New versus Used Electric Vehicle Subsidies

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

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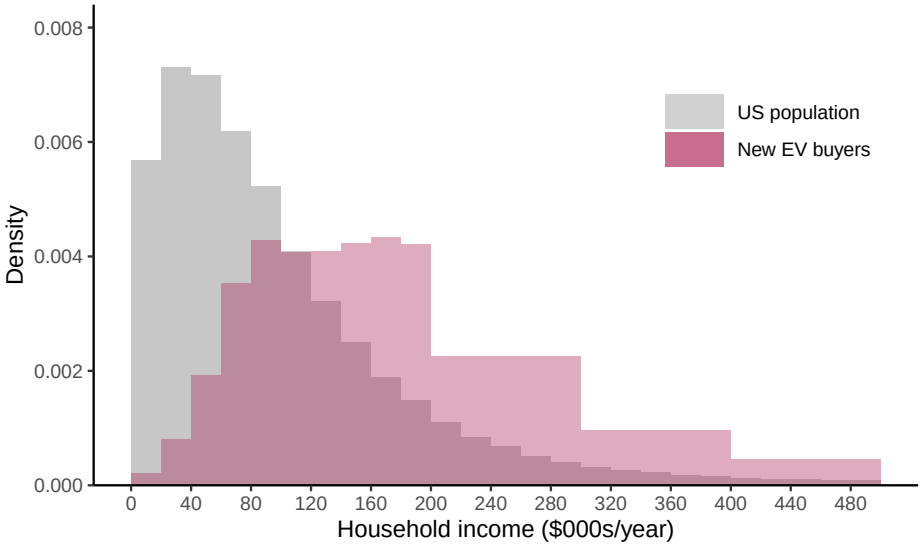
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A Policy Background Appendix

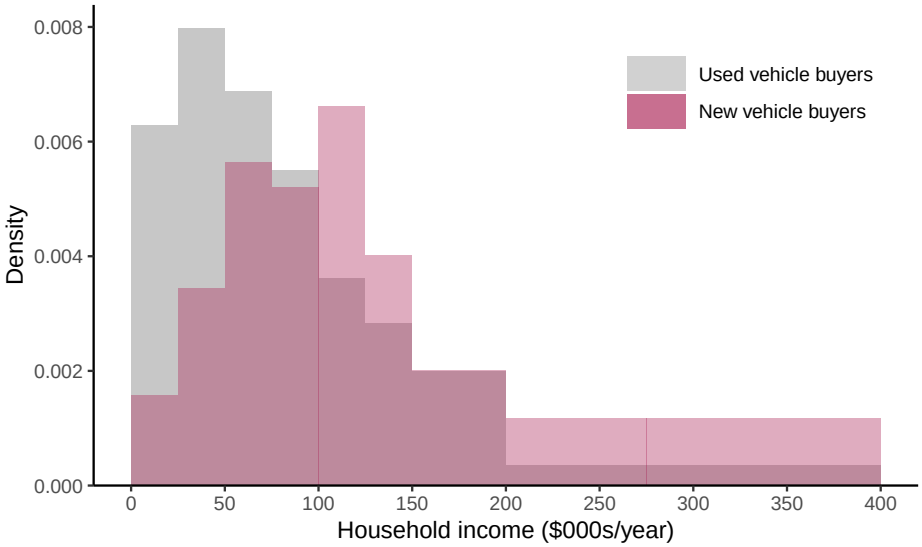
In this appendix we provide additional context to the summary statistics presented in the body by showing the full distributions of income. Panel (a) of Figure A1 presents the household income distributions for new EV buyers versus the U.S. population, using surveys from 2023. This highlights how new 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 are relatively less wealthy than new vehicle buyers, as one would expect.

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

B.1 Proof of Proposition 1

This appendix derives equilibrium price and quantity effects of marginal subsidy changes in steady-state. Throughout we employ two market clearing conditions:

$$D_n(p_n - \mu\tau_n - v(p_u), p_u - \mu\tau_u) = (1-g)D_u(p_n - \mu\tau_n - v(p_u), p_u - \mu\tau_u) \tag{15}$$

$$p_n - c = \frac{-\theta}{D'_n} D_n, \tag{16}$$

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 be used frequently below. Note our regularity condition given in the body is sufficient to guarantee this is positive.

B.1.1 Incidence of new subsidies

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

$$\frac{dp_n}{d\tau_n} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right] + D'_c\frac{dp_u}{d\tau_n}\right) \tag{17}$$

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

Rearranging gives

$$\frac{dp_n}{d\tau_n} = \frac{\mu\theta + \theta(1-g)\frac{dp_u}{d\tau_n} - \theta\frac{dp_u}{d\tau_n}\frac{D'_c}{D'_n}}{1+\theta} \tag{19}$$

$$\frac{dp_n}{d\tau_n} = \frac{\mu(1-g)D'_n - \mu D'_c + \frac{dp_u}{d\tau_n}\left(g'D_n + D'_u - 2(1-g)D'_c + (1-g)^2 D'_n\right)}{(1-g)D'_n - D'_c}. \tag{20}$$

The final incidence values are then

$$\frac{dp_n}{d\tau_n} = \mu\frac{\theta\left(\frac{D'_c D'_c}{D'_n} - D'_u - g'D_n\right)}{\chi} \geq 0 \tag{21}$$

$$\frac{dp_u}{d\tau_n} = \mu\frac{(1-g)D'_n - D'_c}{\chi} \leq 0 \tag{22}$$

B.1.2 Incidence of used subsidies

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

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D'_c\left[\frac{dp_u}{d\tau_u} - \mu\right]\right) \tag{23}$$

$$D'_c\left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) + D'_u\left(\frac{dp_u}{d\tau_u} - \mu\right) = (1-g)\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D'_c\left[\frac{dp_u}{d\tau_u} - \mu\right]\right) - g'D_n\frac{dp_u}{d\tau_u}. \tag{24}$$

Rearranging gives

$$\frac{dp_n}{d\tau_u} = \frac{\theta(1-g)\frac{dp_u}{d\tau_u} - \theta\frac{D'_c}{D'_n}\frac{dp_u}{d\tau_u} + \mu\theta\frac{D'_c}{D'_n}}{1+\theta} \tag{25}$$

$$\frac{dp_n}{d\tau_u} = \frac{\mu(1-g)D'_c - \mu D'_u + \frac{dp_u}{d\tau_u}\left[(1-g)^2D'_n - 2(1-g)D'_c + g'D_n + D'_u\right]}{(1-g)D'_n - D'_c}. \tag{26}$$

Solve this system gives

$$\frac{dp_n}{d\tau_u} = \mu\frac{\theta(1-g)\left[\frac{D'_cD'_c}{D'_n} - D'_u\right] - \theta g'D_n\frac{D'_c}{D'_n}}{\chi} \lesseqgtr 0 \tag{27}$$

$$\frac{dp_u}{d\tau_u} = \mu\frac{(1-g)D'_c - (1+\theta)D'_u + \theta\frac{D'_cD'_c}{D'_n}}{\chi} \geq 0. \tag{28}$$

B.1.3 Quantity effects

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

$$\frac{dp_n}{d\tau_n} = \frac{-\theta}{D'_n}\frac{dD_n}{d\tau_n} \implies \frac{dD_n}{d\tau_n} = \frac{-D'_n}{\theta}\frac{dp_n}{d\tau_n} \geq 0 \tag{29}$$

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\frac{dD_n}{d\tau_u} \implies \frac{dD_n}{d\tau_u} = \frac{-D'_n}{\theta}\frac{dp_n}{d\tau_u} \lesseqgtr 0. \tag{30}$$

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

$$\frac{dD_u}{d\tau_n} = (1-g)\frac{dD_n}{d\tau_n} - g'\frac{dp_u}{d\tau_n}D_n \tag{31}$$

$$= -(1-g)\frac{dp_n}{d\tau_n}\frac{D'_n}{\theta} - g'D_n\frac{dp_u}{d\tau_n} \tag{32}$$

$$= \frac{\frac{-D'_n}{\theta}(1-g)\mu\theta\left(\frac{D'_cD'_c}{D'_n} - D'_u - g'D_n\right) - \mu g'D_n\left((1-g)D'_n - D'_c\right)}{\chi} \tag{33}$$

$$= \mu\frac{(1-g)\left[D'_uD'_n - D'_cD'_c\right] + g'D_nD'_c}{\chi} \lesseqgtr 0 \tag{34}$$

and

$$\frac{dD_u}{d\tau_u} = (1-g)\frac{dD_n}{d\tau_u} - g'\frac{dp_u}{d\tau_u}D_n \tag{35}$$

$$= -(1-g)\frac{dp_n}{d\tau_u}\frac{D'_n}{\theta} - g'\frac{dp_u}{d\tau_u}D_n \tag{36}$$

$$= \frac{\frac{-D'_n}{\theta}(1-g)\mu\theta\left[(1-g)\cdot\left(\frac{D'_cD'_c}{D'_n} - D'_u\right) - g'D_n\frac{D'_c}{D'_n}\right] - \mu g'D_n\left[(1-g)D'_c - (1+\theta)D'_u + \theta\frac{D'_cD'_c}{D'_n}\right]}{\chi} \tag{37}$$

$$= \mu\frac{(1-g)^2\cdot(D'_nD'_u - D'_cD'_c) + g'D_n\left[(1+\theta)D'_u - \theta\frac{D'_cD'_c}{D'_n}\right]}{\chi} \geq 0 \tag{38}$$

B.2 Proof of Proposition 2

We use the steady-state price derivatives given in Appendix B.1 to compute the rent derivatives below.

B.2.1 New vehicle rents

We first differentiate the rents individually

$$\frac{dr_n}{d\tau_n} = \frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n} \tag{39}$$

$$= \frac{-(1-g)D'_c + g'D_n + D'_u}{\chi} < 0 \tag{40}$$

$$\frac{dr_n}{d\tau_u}\frac{1}{1-g} = \frac{1}{1-g}\left[\frac{dp_n}{d\tau_u} - \frac{dp_u}{d\tau_u}\right] \tag{41}$$

$$= \frac{D'_u - (1-g)D'_c - \frac{\theta g'D_nD'_c}{D'_n(1-g)}}{\chi} < 0 \tag{42}$$

Finally if we subtract the two we get

$$\frac{dr_n}{d\tau_n} - \frac{dr_n}{d\tau_u}/(1-g) = \frac{g'D_n + \theta g' D_n \frac{D_c'}{D_n'(1-g)}}{\chi D_n} = \frac{g'D_n\left[1 + \frac{\theta D_c'}{D_n'(1-g)}\right]}{\chi D_n} \tag{43}$$

We want to show that equation (43) is greater than or equal to 0. For this to be true, $D_c' \leq -2(1-g)D_n'/\theta$, which is implied by the assumption in our setup since $\theta \leq 1$.

B.2.2 Used vehicle rent

We first differentiate the rents individually

$$\frac{dr_u}{d\tau_n} = \frac{dp_u}{d\tau_n} = \frac{(1-g)D_n' - D_c'}{\chi} < 0 \tag{44}$$

and

$$\frac{dr_u}{d\tau_u}\frac{1}{1-g} = \frac{1}{1-g}\left[\frac{dp_u}{d\tau_u} - 1\right] \tag{45}$$

$$= \frac{(1-g)D_n' + \frac{(1+\theta)}{1-g}g'D_n - D_c'}{\chi} < 0. \tag{46}$$

Combining we get

$$\frac{dr_u}{d\tau_n} - \frac{dr_u}{d\tau_u}/(1-g) = -\frac{\frac{(1+\theta)}{1-g}g'D_n}{\chi D_n} > 0, \tag{47}$$

which indicates that used subsidies decrease used rent r_u more, as we needed to show.

B.3 Proof of Proposition 3

To prove this, it is sufficient to notice that equations (43) and (47), which were used when solving for the relative rent derivatives in the general case, are both 0 when $g' = 0$. This proves the rent derivatives, as presented in the proposition, are equal.

B.4 Short-Run Effects

Most of the theory focuses 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. Appendix B.4.1 presents the full set of results. Proposition 6 presents a key result motivating our bunching estimator in Section 5.

Proposition 6. *Assume $g' = 0$ and $D'_c = 0$. Then the effect of a surprise subsidy τ_{ut} announced at the beginning of period t is*

$$\Delta p_{ut} = \mu \tau_{ut}.$$

Proof: see Appendix B.4.1.

Proposition 6 states that if supply to used vehicle buyers (including scrappage) is fully inelastic and there is no new-used substitution, then the used vehicle price increases one-for-one with the subsidy, after adjusting for the share of buyers that are eligible. In Appendix B.4.1, we show that elastic scrappage and new-used substitution both reduce $\frac{dp_{ut}}{d\tau_u}$.

B.4.1 Proof of Proposition 6

We model the short-run market as having exogenous used EV supply $S^u = D_{n,t-1}$. The market clearing conditions are then

$$p_{nt} - c = \frac{-\theta}{D'_n} D_n(p_{nt} - \tau_{nt} - \tilde{r}_{t+1}(\tilde{p}_{u,t+1}), p_{ut} - \tau_{ut}) \tag{48}$$

$$(1 - g_t)S^u = D_u(p_{nt} - \tau_{nt} - \tilde{r}_{t+1}(\tilde{p}_{u,t+1}), p_{ut} - \tau_{ut}). \tag{49}$$

Within this system, $\tilde{g}_{t+1}$ and $\frac{d\tilde{p}_{u,t+1}}{d\tau_u}$ are unknown quantities since the market may not equilibrate in the next period. These are based on actor's expectations regarding the next period prices.

We drop the t subscripts below when they indicate the current period.

As we desire $\frac{dp_u}{d\tau_u}$, we totally differentiate the market clearing conditions with respect to τ_u, yielding

$$\frac{dp_n}{d\tau_u} = \frac{-\theta}{D'_n}\left(D'_n\left[\frac{dp_n}{d\tau_u} - (1 - \tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u}\right] + D'_c\left[\frac{dp_u}{d\tau_u} - \mu\right]\right) \tag{50}$$

$$-g'\frac{dp_u}{d\tau_u}S'_u = D'_c\left[\frac{dp_n}{d\tau_u} - (1 - \tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u}\right] + D'_u\left[\frac{dp_u}{d\tau_u} - \mu\right]. \tag{51}$$

Rearranging yields

$$\frac{dp_n}{d\tau_u} = \frac{\theta(1 - \tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u} - \theta\frac{D'_c}{D'_n}\frac{dp_u}{d\tau_u} + \theta\mu\frac{D'_c}{D'_n}}{1 + \theta} \tag{52}$$

$$\frac{dp_n}{d\tau_u} = \frac{D'_c(1 - \tilde{g}_{t+1})\frac{d\tilde{p}_{u,t+1}}{d\tau_u} - D'_u\frac{dp_u}{d\tau_u} + \mu D'_u - g'\frac{dp_u}{d\tau_u}S^u}{D'_c}. \tag{53}$$

Define the quantity $\chi_{SR} = \theta\frac{D'_c D'_c}{D'_n} - (1 + \theta) \cdot (D'_u + g'S) \geq 0$. Solving this system leads to

$$\frac{dp_n}{d\tau_u} = \frac{\theta(1-\tilde{g}_{t+1})\frac{d\tilde{p_u},t+1}{d\tau_u}\left[\frac{D_c' D_c'}{D_n'} - D_u' - g' S^u\right] - \mu\theta\frac{D_c'}{D_n'} g' S^u}{\chi_{SR}} \tag{54}$$

$$\frac{dp_u}{d\tau_u} = \frac{\mu\left(\theta\frac{D_c' D_c'}{D_n'} - (1+\theta)D_u'\right) - D_c'(1-\tilde{g}_{t+1})\frac{d\tilde{p_u},t+1}{d\tau_u}}{\chi_{SR}}. \tag{55}$$

If we suppose $D_c' = 0$ and $g' = 0$, then $\frac{dp_u}{d\tau_u} = \mu$, as we wanted to show.

Adding $D_c' > 0$ and $g' < 0$ serves to increase the denominator and decrease the numerator (to the extent that $\frac{d\tilde{p_u},t+1}{d\tau_u} \geq 0$ as one would expect), implying these moderate the pass-through rate of the subsidy.

B.5 Proof of Proposition 4

One period of welfare W can be expressed as

$$W = w_i CS_i + D_n(p_n - c + \phi + \phi_n - \tau_n) + D_u(\phi - \tau_u), \tag{56}$$

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

$$\frac{dCS}{d\bar{p}_x} = \lambda(\bar{p}_n, \bar{p}_u)\frac{\partial B}{\partial \bar{p}_x} = -\lambda \cdot D_x, \tag{57}$$

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

$$\frac{dCS(\bar{p_n}, \bar{p_u})}{d\tau_x} = \frac{dCS}{d\bar{p_n}}\frac{d\bar{p_n}}{d\tau_x} + \frac{dCS}{d\bar{p_u}}\frac{d\bar{p_u}}{d\tau_x} = -D_n \cdot \frac{d(p_n - \tau_n - r)}{d\tau_x} - D_u \cdot \frac{d(p_u - \tau_u - r^s)}{d\tau_x}, \tag{58}$$

for both τ_n and τ_u.

We now differentiate with respect to τ_n and τ_u,

$$\frac{dW}{d\tau_n} = -\sum_i w_i \left[D_{in} \cdot \left(\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n} \right) + D_{iu} \cdot \frac{dp_u}{d\tau_n} \right] + D_n \cdot \left(\frac{dp_n}{d\tau_n} - 1 \right)$$
$$+ \frac{dD_n}{d\tau_n} \cdot (p_n - c + \phi - \tau_n) + \frac{dD_u}{d\tau_n}(\phi - \tau_u) \tag{59}$$
$$\frac{dW}{d\tau_u} = -\sum_i w_i \left[D_{in} \cdot \left(\frac{dp_n}{d\tau_n} - (1-g)\frac{dp_u}{d\tau_u} \right) + D_{iu} \cdot \left(\frac{dp_u}{d\tau_u} - 1 \right) \right] + D_n \cdot \frac{dp_n}{d\tau_u} \tag{60}$$
$$+ \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n) - D_u + \frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u). \tag{61}$$

Rearranging and simplifying gives

$$\sum_j \frac{dD_j}{d\tau_n}(p_j - c_j + \phi - \tau_j) = \left(D_n - \sum_i w_i D_{in} \right) + \frac{dp_n}{d\tau_n} \left(\sum_i w_i D_{in} - D_n \right) + \frac{dp_u}{d\tau_n} \left(\sum_i w_i D_{iu} - \sum_i w_i D_{in}(1-g) \right) \tag{62}$$

$$\sum_j \frac{dD_j}{d\tau_u}(p_j - c_j + \phi - \tau_j) = \left(D_u - \sum_i w_i D_{iu} \right) + \frac{dp_n}{d\tau_u} \left(\sum_i w_i D_{in} - D_n \right) + \frac{dp_u}{d\tau_u} \sum_i (w_i D_{iu} - (1-g) w_i D_{in}), \tag{63}$$

where $j \in \{n, u\}$ and $p_u = c_u$.

Recognize that

$$\frac{\sum_i w_i D_{in}}{D_n} = 1 - Cov\left(\frac{w_i}{\bar{w}}, \frac{D_{in}}{\bar{D}_n} \right) \quad \text{and} \quad \frac{\sum_i w_i D_{iu}}{D_n} = (1-g) \cdot \left[1 - Cov\left(\frac{w_i}{\bar{w}}, \frac{D_{iu}}{\bar{D}_u} \right) \right], \tag{64}$$

where the $\bar{(\cdot)}$ denotes averages and provided $\bar{w} = 1$, which we assume.

We can then simplify the two FOCs further:

$$\frac{\frac{dD_n}{d\tau_n} \cdot (p_n - c + \phi + \phi_n - \tau_n)}{D_n} + \frac{\frac{dD_u}{d\tau_n} \cdot (\phi - \tau_u)}{D_n} = \theta_n \cdot \frac{dr_n}{d\tau_n} + \theta_u (1-g) \frac{dr_u}{d\tau_n} \tag{65}$$
$$\frac{\frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi + \phi_n - \tau_n)}{D_n} + \frac{\frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u)}{D_n} = \theta_n \cdot \frac{dr_n}{d\tau_u} + \theta_u (1-g) \frac{dr_u}{d\tau_u}, \tag{66}$$

and isolate τ_n:

$$\tau_n = (p_n - c + \phi + \phi_n) + \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} \cdot (\phi - \tau_u) - \frac{D_n}{\frac{dD_n}{d\tau_n}} \left[\theta_n \frac{dr_n}{d\tau_n} + \theta_u (1-g) \frac{dr_u}{d\tau_n} \right] \tag{67}$$
$$\tau_n = (p_n - c + \phi + \phi_n) + \frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} \cdot (\phi - \tau_u) - \frac{D_n}{\frac{dD_n}{d\tau_u}} \left[\theta_n \frac{dr_n}{d\tau_u} + \theta_u (1-g) \frac{dr_u}{d\tau_u} \right]. \tag{68}$$

This is two equations with two unknowns, so we can solve for τ_n and τ_u. Before solving, we make the assumption that

$$\frac{dD_u}{d\tau_n}/\frac{dD_n}{d\tau_n} - \frac{dD_u}{d\tau_u}/\frac{dD_n}{d\tau_u} \leq 0, \tag{69}$$

which says that own demand derivatives are larger than cross demand derivatives. Solving for τ_u^* yields

$$\tau_u^* = \phi + D_n \left[\theta_n \left(\frac{\frac{dr_n}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dr_n}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right) + (1-g)\theta_u \left(\frac{\frac{dr_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dr_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right)\right] / \left[\underbrace{\frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} - \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}}}_{\geq 0}\right]. \tag{70}$$

Since $\theta_n \leq 0$ and $\theta_u \geq 0$ by assumption, this equation makes it clear how the optimal τ_u^* depends on the magnitudes of the rent derivatives.

Solving for τ_n^* yields

$$\tau_n^* = p_n - c + \phi + \phi_n - \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} D_n \left[\theta_n \left(\frac{\frac{dr_n}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dr_n}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right) + (1-g)\theta_u \left(\frac{\frac{dr_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dr_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right)\right] / \left[\underbrace{\frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} - \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}}}_{\geq 0}\right] \tag{71}$$

$$- D_n \left[\theta_n \frac{\frac{dr_n}{d\tau_n}}{\frac{dD_n}{d\tau_n}} + \theta_u (1-g) \frac{\frac{dr_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}}\right], \tag{72}$$

which has the opposite sign dependencies than τ_u^* above.

B.6 Proof of Proposition 5

In order to prove this result, we need to know the signs of the steady-state pass-through rates under the condition that $\mu_n \neq \mu_u$ but are exogenous to τ_n and τ_u. The steady-state rates from Proposition 1 hold with constant μ across markets and just multiply the full eligibility pass-through rates. Since we only need to show this result for $\mu_u - \mu_n \leq C \in \mathbb{R}^{>0}$, by continuity, we can assume the signs of the pass-through rates remain.

B.6.1 Proof of Restricted New vs Used Subsidies

For brevity in the main body, we add additional framework here. Let N_l and N_h denote the number of people in each group. We assume the welfare weight applied to producer surplus, externalities, and government

expenditure is the average welfare weight (which for G is equivalent to excess tax revenue being returned uniformly to consumers). Let $(1+w_h)$ and $(1+w_l)$ denote the welfare weight on the high- and low-income groups, respectively. WLOG we normalize the average welfare weight to be 1, so $w_h/w_l = N_l/N_h$. Under this formulation, we can state the welfare function assuming the low-income group is always eligible

$$W \coloneqq (1-w_h)\cdot CS^h + (1+w_l)\cdot CS^l + (D_{hn}+D_{ln})\cdot(p_n - c + \phi + \phi_n) - \tau_n(D_{ln} + D_{hn}\cdot \mathbb{1}_{\{\mu_u=1\}}) \\ + \phi\cdot(D_{hu}+D_{lu}) - \tau_u(D_{lu} + D_{hu}\cdot\mathbb{1}_{\{\mu_u=1\}}). \tag{73}$$

CS denotes consumer surplus which we can differentiate via the envelope theorem per the prior welfare proposition.

Before we compute the welfare derivatives, note that μ_n and μ_u are endogenous to our model, but any derivative of μ will be multiplied by a factor of τ_n or τ_u. Therefore, by assuming that $\tau_n = \tau_u = 0$ as our starting position, we can assume μ_n and μ_u are fixed in our analysis below.

We first compare restricted new and used subsidies where we assume only the low-income group is eligible. Differentiating the welfare function gives the following result

$$\frac{dW}{d\tau_n} = -(1-w_h)\cdot\left(D_{hn}\cdot(\frac{dp_n}{d\tau_n} - (1-g)\frac{dp_u}{d\tau_n}) + D_{hu}\cdot(\frac{dp_u}{d\tau_n})\right) - (1+w_l)D_{ln}\cdot(\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}) \\ - (1-w_l)D_{lu}\cdot(\frac{dp_u}{d\tau_n}) + (D_{hn}+D_{ln})\cdot(\frac{dp_n}{d\tau_n}) + \left(\frac{dD_{hn}}{d\tau_n} + \frac{dD_{ln}}{d\tau_n}\right)\cdot(p_n - c + \phi) \\ - \frac{dD_{ln}}{d\tau_n}\tau_n - D_{ln} + \frac{dD_{hu}}{d\tau_n}\cdot(\phi) + \frac{dD_{lu}}{d\tau_n}(\phi - \tau_u) \tag{74}$$

$$\frac{dW}{d\tau_u} = -(1-w_h)\cdot\left(D_{hn}\cdot(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}) + D_{hu}\cdot(\frac{dp_u}{d\tau_u})\right) - (1+w_l)D_{ln}\cdot(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}) \\ - (1-w_l)D_{lu}\cdot(\frac{dp_u}{d\tau_u} - 1) + (D_{hn}+D_{ln})\cdot(\frac{dp_n}{d\tau_u}) + \left(\frac{dD_{hn}}{d\tau_u} + \frac{dD_{ln}}{d\tau_u}\right)\cdot(p_n - c + \phi) \\ - \frac{dD_{ln}}{d\tau_u}\tau_n + \left(\frac{dD_{hu}}{d\tau_u} + \frac{dD_{lu}}{d\tau_u}\right)(\phi) - \tau_u\frac{dD_{lu}}{d\tau_u} - D_{lu}. \tag{75}$$

Simplifying and evaluating the derivative at $(\tau_n, \tau_u) = (0,0)$, we get

$$\frac{dW}{d\tau_n} = w_l D_{ln} + \frac{dp_n}{d\tau_n}\cdot(w_h D_{hn} - w_l D_{ln}) + \frac{dp_u}{d\tau_n}\cdot[(1-g)(w_l D_{ln} - w_h D_{hn}) - (w_l D_{lu} - w_h D_{hu})] \\ + \frac{dD_{hn}}{d\tau_n}\cdot(p_n - c + \phi) + \frac{dD_{ln}}{d\tau_n}\cdot(p_n - c + \phi) + \frac{dD_{hu}}{d\tau_n}\phi + \frac{dD_{lu}}{d\tau_n}(\phi) \tag{76}$$

$$\frac{dW}{d\tau_u} = w_l D_{lu} + \frac{dp_n}{d\tau_u}\cdot(w_h D_{hn} - w_l D_{ln}) + \frac{dp_u}{d\tau_u}\cdot[(1-g)(w_l D_{ln} - w_h D_{hn}) - (w_l D_{lu} - w_h D_{hu})] \\ + \frac{dD_{hn}}{d\tau_u}\cdot(p_n - c + \phi) + \frac{dD_{ln}}{d\tau_u}\cdot(p_n - c + \phi) + \frac{dD_{hu}}{d\tau_u}\phi + \frac{dD_{lu}}{d\tau_u}(\phi). \tag{77}$$

Since the subsidies are restricted to the low-income groups, $\frac{dG}{d\tau_n} = D_{ln}$ and $\frac{dG}{d\tau_u} = D_{lu}$. Before proving the main result, we first consider two intermediate terms:

$$w_h D_{hn} - w_l D_{ln} = w_l \cdot (D_{hn} \cdot \frac{N_l}{N_h} - D_{ln}) > 0, \tag{78}$$

$$\begin{aligned}(1-g)(w_l D_{ln} - w_h D_{hn}) - (w_l D_{lu} - w_h D_{hu}) &= w_l \left[(1-g)D_{ln} - D_{lu}\right] + w_h \left[D_{hu} - (1-g)D_{hn}\right] \\ &= (w_l + w_h) \cdot \left[(1-g)D_{ln} - D_{lu}\right] < 0, \end{aligned} \tag{79}$$

where the sign is implied by our assumptions given in the main body.

Our goal is to show that $\frac{dW}{d\tau_n}/\frac{dG}{d\tau_n} - \frac{dW}{d\tau_u}/\frac{dG}{d\tau_u} > 0$, we prove this by breaking the expression into three terms and showing each one is positive. We also explain what each term means intuitively.

Term 1: $(w_h D_{hn} - w_l D_{ln}) \cdot (\frac{dp_n}{d\tau_n}/D_{ln} - \frac{dp_n}{d\tau_u}/D_{lu}) > 0$. The first parenthesis group is positive from equation (78), while for the second we see that $\frac{dp_n}{d\tau_n} \geq \frac{dp_n}{d\tau_u}$ from Proposition 1 if $\mu_u = \mu_n$, so by continuity there exists a C such that if $\mu_u - \mu_n \geq C$ then this remains true. We assume $D_{ln} < D_{lu}$ in our setup.

This terms originates from producer surplus having a welfare weight between the low- and high-income groups, implying that increasing p_n is welfare-improving, assuming fixed quantities, because new vehicles are predominantly bought by high-income buyers.

Term 2: $\underbrace{(\frac{dp_u}{d\tau_n}/D_{ln} - \frac{dp_u}{d\tau_u}/D_{lu})}_{<0} \cdot \underbrace{\left[(1-g)(w_l D_{ln} - w_h D_{hn}) - (w_l D_{lu} - w_h D_{hu})\right]}_{<0} > 0$. This term is unambiguously positive since $\frac{dp_u}{d\tau_n} \leq 0$ and $\frac{dp_u}{d\tau_u} \geq 0$, while the second grouping is negative by equation (79). This term is related to resale value changes. Note that decreasing p_u represents a transfer from new vehicle sellers, which are predominantly high-income, to used vehicle buyers, which are predominantly low-income, thus decreasing p_u is welfare increasing. This term is positive since new subsidies decrease p_u while used subsidies increase p_u.

Term 3: Demand derivatives. In full, the demand derivatives read

$$\left(\frac{\frac{dD_{hn}}{d\tau_n} + \frac{dD_{ln}}{d\tau_n}}{D_{ln}} - \frac{\frac{dD_{hn}}{d\tau_u} + \frac{dD_{ln}}{d\tau_u}}{D_{lu}}\right) \cdot \left[p_n - c + \phi + \phi_n\right] + \phi \cdot \left(\frac{\frac{dD_{hu}}{d\tau_n} + \frac{dD_{lu}}{d\tau_n}}{D_{ln}} - \frac{\frac{dD_{hu}}{d\tau_u} + \frac{dD_{lu}}{d\tau_u}}{D_{lu}}\right). \tag{80}$$

The equivalence result shows that when $g' = 0$ and μ is uniform, then the scaled rent derivatives are equal. This implies that $\frac{dD_x}{d\tau_u} = (1-g)\frac{dD_x}{d\tau_n}$ for $x \in \{n, u\}$, and these are both positive. Therefore, we know that $\frac{dD_n}{d\tau_n}/D_{ln} > \frac{dD_u}{d\tau_n}/D_{lu}$ which is sufficient for this term to be positive. By continuity, if μ_n and μ_u are close enough, then this term will remain positive.

Intuitively, this term is saying that new subsidies will create the same demand derivative as used subsidies, but they target a smaller population so they are more cost effective. This implicitly relies on all consumers being at an interior solution.

B.6.2 Restricted vs Unrestricted Used Subsidies

The derivation of the unrestricted welfare derivative is analogous to that in equation (77). The unrestricted case adds an additional $-w_h D_{hu}$ reflecting the negative effect of direct transfers to the high-income group. Now suppose $\mu_n = \mu_u = \mu$, then everything except $w_l D_{lu}$ scales linearly in equation (77) with μ. So evaluating at $\tau_n = \tau_u = 0$, we get

$$\frac{dW}{d\tau_{u_{|\mu_u=1}}} = \frac{dW}{d\tau_u}\frac{1}{\mu} - \frac{1}{\mu}w_l D_{lu} + w_l D_{lu} - w_h D_{hu}. \tag{81}$$

Note that in the restricted case, $dG/d\tau_u = D_{lu}$ while $dG/d\tau_u = D_u$ in the unrestricted case. But μ is the share of eligible buyers (assuming this is the same in both markets), thus $\mu = D_{lu}/D_u$. Thus combined we have

$$\frac{dW}{d\tau_{u_{|\mu_u=1}}}/\frac{dG}{d\tau_{u_{|\mu_u=1}}} = \frac{dW}{d\tau_u}/\frac{dG}{d\tau_u} + \frac{1}{D_u}\cdot\left(\frac{-1}{\mu}w_l D_{lu} + w_l D_{lu} - w_h D_{hu}\right) \leq \frac{dW}{d\tau_u}/\frac{dG}{d\tau_u}. \tag{82}$$

By continuity there exists a $C > 0$ such that if $\mu_u - \mu_n \leq C$, then $\frac{dW}{d\tau_u}/\frac{dG}{d\tau_u} > \frac{dW}{d\tau_{u_{|\mu_u=1}}}/\frac{dG}{d\tau_{u_{|\mu_u=1}}}$, as we wanted to show.

B.7 Uniform Weighted Optimal Policy with GV Markups

We now partially extend the setup given in Section 3.1 to include GVs. Specifically, we assume they have new demand D_n^G and used demand D_u^G. Let G superscripts denote the GV variant of parameters (i.e. p_n^G is the price of new GVs). We allow flexible substitution by assuming that D_n, D_u, D_n^G, D_u^G are functions of the four vehicle rents. Furthermore, we assume there is a fixed market size N, which justifies maintaining ϕ as the relative externality reduction of EVs.

Under these assumptions, we can express welfare as

$$W = CS + D_n \cdot (p_n - c + \phi - \tau_n) + D_u(\phi - \tau_u) + D_n^G \cdot (p_n^G - c^G), \tag{83}$$

where CS is consumer surplus. We can now differentiate, where we use the envelope theorem on consumer surplus, as we did above,

$$\frac{dW}{d\tau_n} = -D_n \cdot \left(\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}\right) - D_u\frac{dp_u}{d\tau_n} - D_n^G \cdot \left(\frac{dp_n^G}{d\tau_n} - (1-g^G)\frac{dp_u}{d\tau_n}\right) - D_u^G\frac{dp_u^G}{d\tau_n} + D_n \cdot \left(\frac{dp_n}{d\tau_n} - 1\right) + \frac{dD_n}{d\tau_n} \cdot (p_n - c + \phi - \tau_n) + \frac{dD_u}{d\tau_n} \cdot (\phi - \tau_u) + \frac{dD_n^G}{d\tau_n} \cdot (p_n^G - c^G) + D_n^G\frac{dp_n^G}{d\tau_n} \tag{84}$$

$$\frac{dW}{d\tau_u} = -D_n \cdot \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) - D_u\left(\frac{dp_u}{d\tau_u} - 1\right) - D_n^G \cdot \left(\frac{dp_n^G}{d\tau_u} - (1-g^G)\frac{dp_u}{d\tau_u}\right) - D_u^G\frac{dp_u^G}{d\tau_u} + D_n\frac{dp_n}{d\tau_u} + \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n) - D_u + \frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u) + \frac{dD_n^G}{d\tau_u} \cdot (p_n^G - c^G) + D_n^G\frac{dp_n^G}{d\tau_u}. \tag{85}$$

Simplifying these expressions leads to

$$\tau_n = p_n - c + \phi + (\frac{dD_u}{d\tau_n}/\frac{dD_n}{d\tau_n}) \cdot (\phi - \tau_u) + \frac{dD_n^G}{d\tau_n}/\frac{dD_n}{d\tau_n} \cdot (p_n^G - c^G) \tag{86}$$

$$\tau_n = p_n - c + \phi + (\frac{dD_u}{d\tau_u}/\frac{dD_n}{d\tau_u}) \cdot (\phi - \tau_u) + \frac{dD_n^G}{d\tau_u}/\frac{dD_n}{d\tau_u} \cdot (p_n^G - c^G). \tag{87}$$

To proceed further, we now make two assumptions. First, we assume that own-demand derivatives are larger than cross-demand derivatives, formally:

$$\frac{dD_u^E}{d\tau_u}/\frac{dD_n^E}{d\tau_u} > \frac{dD_u^E}{d\tau_n}/\frac{dD_n^E}{d\tau_n}. \tag{88}$$

This is plausible since the own-price rents change by more than the cross-price rents, per Proposition 2. Second, EV quantities rise less per unit $\frac{dD_n}{d\tau_n}$ than per unit $\frac{dD_n}{d\tau_u}$ because the former raises the EV scrap rate. Therefore, if we assume the GV scrap rate is relatively inelastic, this implies that

$$\frac{dD_n^G}{d\tau_u}/\frac{dD_n^E}{d\tau_u} < \frac{dD_n^G}{d\tau_n}/\frac{dD_n^E}{d\tau_n} < 0. \tag{89}$$

Using these two assumptions, we can solve for τ_u from the two simplified FOCs,

$$0 = \underbrace{\left(\frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right)}_{<0} \cdot (\phi - \tau_u) + \underbrace{\left(\frac{\frac{dD_n^G}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dD_n^G}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right)}_{>0} \cdot (p_n^G - c^G). \tag{90}$$

Thus as the GV markup increases, τ_u must decrease.

Now consider τ_n, we have the following relationship

$$\tau_n = p_n - c + \phi + (p_n^G - c^G)\frac{dD_u}{d\tau_n}/\frac{dD_n}{d\tau_n} \cdot \left(\frac{\frac{dD_n^G}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dD_n^G}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right) / \left(\frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} - \frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}}\right) + \frac{dD_n^G}{d\tau_n}/\frac{dD_n}{d\tau_n} \cdot (p_n^G - c^G) \tag{91}$$

Now consider what happens if $p_n - c$ and $p_n^G - c^G$ each increase by one, then

$$\Delta\tau_n = 1 + \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} \cdot \frac{-d\tau_u}{d(p_n^G - c^G)} + \frac{dD_n^G}{d\tau_n}/\frac{dD_n}{d\tau_n}. \tag{92}$$

A sufficient condition for $\Delta\tau_n \geq 0$ is for $\frac{dD_n^G}{d\tau_n}/\frac{dD_n}{d\tau_n} \geq -1$, which is plausible given τ_n will raise EV scrap rates.

In sum, this shows that under a few condition, raising the average level of the markup will increase the optimal τ_n and lower τ_u.

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 or 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 assume that any transactions that Experian classifies as "new" to be 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).

D Reduced-Form Appendix

D.1 Event Study Estimator

D.1.1 Empirical Strategy

Our event study estimators use a triple-differences design that compares the prices of EVs versus GVs, below versus above the $25,000 price limit, pre versus post January 1 of 2023 or 2024.

Because the tax credits affect transaction prices, we cannot assign treatment and control groups using the actual transaction price. Instead, we assign treatment status based on predicted transaction prices. Let i index transactions, b index brands, j index models, y index model years, d index dealerships, t index months of sample, and m index months of year. Define p_i as the price, M_i as the vehicle odometer reading, and γ_{bm}, γ_j, and γ_d, respectively, as brand-by-month of year, model, and dealership fixed effects. The prediction regression is

$$\ln(p_i) = \beta \ln(M_i) + \gamma_{bm} + \gamma_j + \gamma_y + \gamma_d + \epsilon_i. \tag{93}$$

We estimate separate predictions for the 2023 versus 2024 event studies, using only data from the year before the event (i.e., 2022 or 2023, respectively). Table A1 shows the coefficient on odometer and the fixed effects, along with observation count. The predicted price is then $\hat{p}_i = \exp(\widehat{\ln(p_i)})$.

The event study regression is the same as the price prediction regression, except with the addition of the triple difference variables and the substitution of month-of-sample effects (indexed t) for month-of-year effects (indexed m). For each year's event study, the post period is January through July of that year, the pre period is July through December of the previous year, and the regression sample is the 13-month period from July to July. 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 PE_i as an indicator for whether the transaction is predicted to be eligible given its predicted price. We set $PE_i = 1$ for $\hat{p}_i \leq \$21,000$ and $PE_i = 0$ for $35,000 \leq \hat{p}_i \leq \$50,000$, and we exclude transactions in all other predicted price ranges.

The event study regression is

$$\begin{aligned} \ln(p_i) = {} & \beta_1 A_t EV_j PE_i + \beta_2 A_t EV_j + \beta_3 A_t PE_i + \beta_4 EV_j PE_i + \beta_5 PE_i \\ & + \beta_6 \ln(M_i) + \gamma_{bt} + \gamma_j + \gamma_y + \gamma_d + \epsilon_i. \end{aligned} \tag{94}$$

We cluster standard errors by model.

The regression samples include only model years that could be eligible for the used EV tax credit in the post period: model year 2021 and earlier for the 2023 event study, and model year 2022 and earlier for the

2024 event study. Thus, in the triple difference specification, the coefficient on β_1 can be interpreted as the average increase in ln(price) for eligible EV transactions in the post period relative to the pre period.

D.1.2 Results

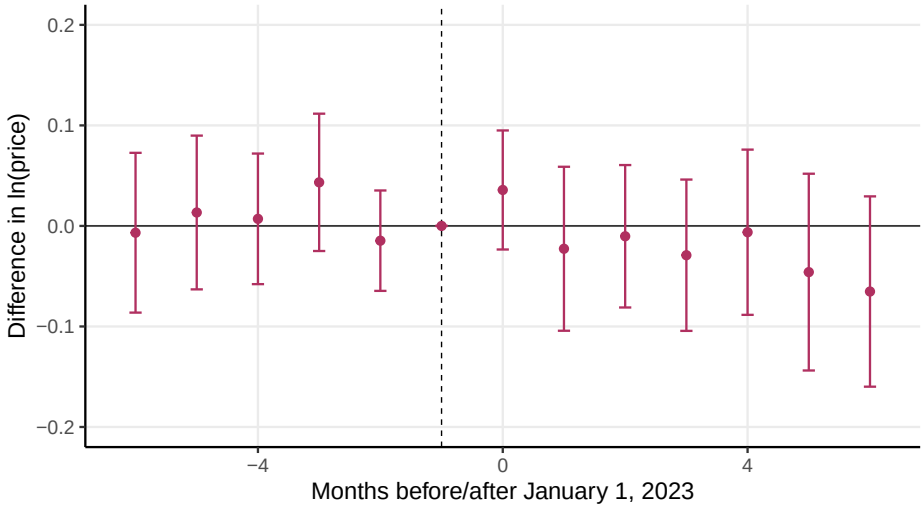
Figure A2 presents the β_1 coefficients in the event study specifications. Panel (a) suggests no statistically detectable price changes for predicted-eligible EVs after the used EV tax credit began in January 2023. Using the pre-post specification reported in Table A2, we estimate a statistically insignificant price change of -0.03 log units, and the 95 percent confidence interval rules out effects of more than 0.04 log units. For a vehicle that would have cost $20,000 before January 2023, this estimate rules out a price increase of more than $750 with 95 percent confidence.

Panel (b) suggests a possible price increase within a few months after dealership transfer began in January 2024. However, the omitted month (December 2023) is a low outlier, making the event study β_1 coefficients harder to interpret. In the pre-post specification reported in Table A3, we estimate that the prices of predicted-eligible EVs increased by 0.02 log units, with a 95 percent confidence interval ruling out increases of more than 0.06 log units. For a vehicle that would have cost $20,000 before January 2024, we reject a price increase of more than $1,229 with 95 percent confidence.

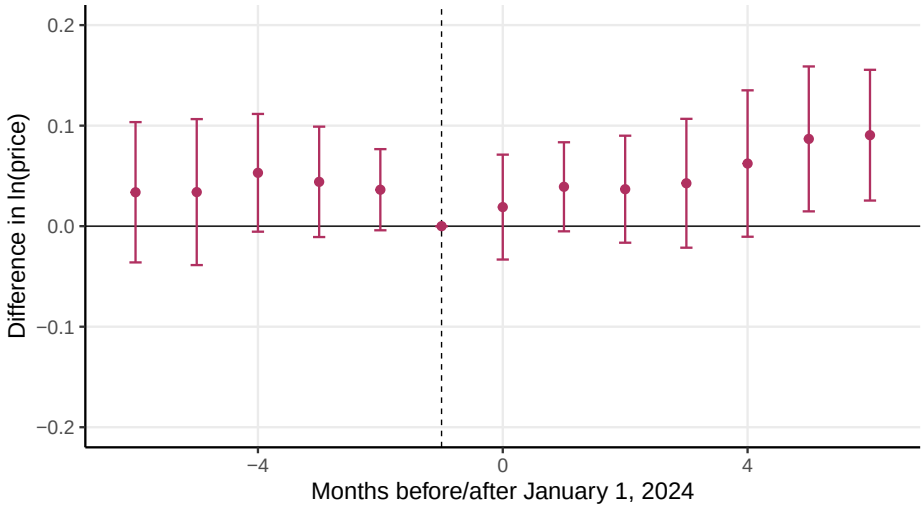
The event study analyses should be interpreted with the following caveats. First, we estimate price changes over a relatively short window of six months after the policy change, and price effects may be different over a longer time horizon. Second, both new and used vehicle markets were very tight in late 2022 before developing more excess supply in 2023, and prices evolved accordingly. The multiple control groups in our triple-difference design are designed to help address concerns, but β_1 would be biased if such market trends affected EVs and less-valuable vehicles differently than GVs and more-valuable vehicles. Third, as illustrated by Proposition 5, eligiblity changes for the new EV tax credit in January 2023 should have affected used EV prices at least marginally, and these effects could also be different for more- versus less-valuable used EVs. Fourth, even without confounding trends, used EV tax credits could also affect ineligible vehicles' prices in equilibrium, so we should interpret β_1 as the relative change between less- versus more-valuable EVs, not as an absolute change for less-valuable EVs. Fifth, since the policy changes were announced months in advance, in principle there could have been anticipation effects, for example if income-eligible people waited until January 2023 to buy used EVs. We find no statistically detectable evidence of this; see Appendix D.2. These limitations help motivate our bunching estimator

Figure A2: **Price Trends for Predicted-Eligible EVs in January 2023 and 2024**

(a) 2023



(b) 2024



Notes: This figure presents β_1 coefficients from the event study estimator in equation (94), interpreted as the price trend 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.

D.2 Tests of Selection Effects in 2023 and 2024

This section presents tests for selection effects and market composition changes following the tax credit implementation. The primary concern is that the tax credit may affect the used EV market through channels other than transaction prices, such as buyer or vehicle composition. The income eligibility requirement could change the composition of buyers purchasing eligible vehicles. If eligible buyers anticipate the policy, they may delay purchases until the credit takes effect, leading to changes in transaction quantities around the implementation dates. Additionally, since only dealership purchases qualify for the credit, the share of transactions occurring through dealerships versus private sales may shift. Finally, dealerships might adjust financing terms rather than upfront prices in response to the policy.

To address these concerns, we test whether the policy affects financing terms measured by annual percentage rates, buyer income, transaction quantities, and the share of transactions occurring through dealerships. We find limited evidence of changes in these characteristics around the policy implementation, alleviating concerns about selection effects for the event study analysis in Appendix D.1.

D.2.1 Financing Terms

To test for policy effects on financing terms, we implement the event study specification described in Appendix D.1.1 with the annual percentage rate (APR) as the outcome variable. Figure A3 presents the β_1 coefficients in the APR event study specifications.

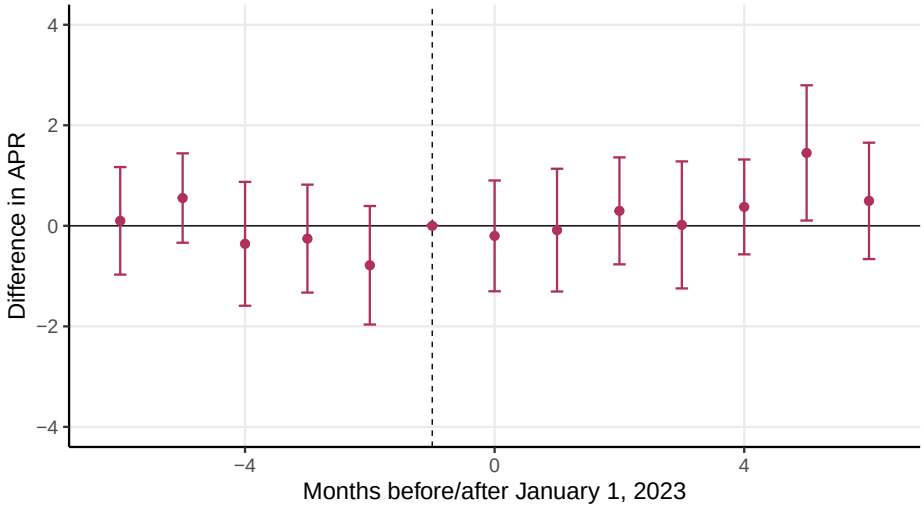
Panel (a) suggests no statistically detectable changes in APR for predicted-eligible EVs after the used EV tax credit began in January 2023, except for a high outlier in May 2023. Based on the pre-post specification reported in Table A2, we reject APR increases of more than 0.943 percent with 95 percent confidence. As comparison, the mean APR in the treatment group of cheap EVs is 10.58 percent. Panel (b) suggests no statistically detectable changes in APR for predicted-eligible EVs directly after the dealership transfer began in January 2024, followed by an increase in the later months of the post-period. Based on the pre-post specification reported in Table A3, we reject APR increases of more than 1.29 percent with 95 percent confidence.

D.2.2 Buyer Income

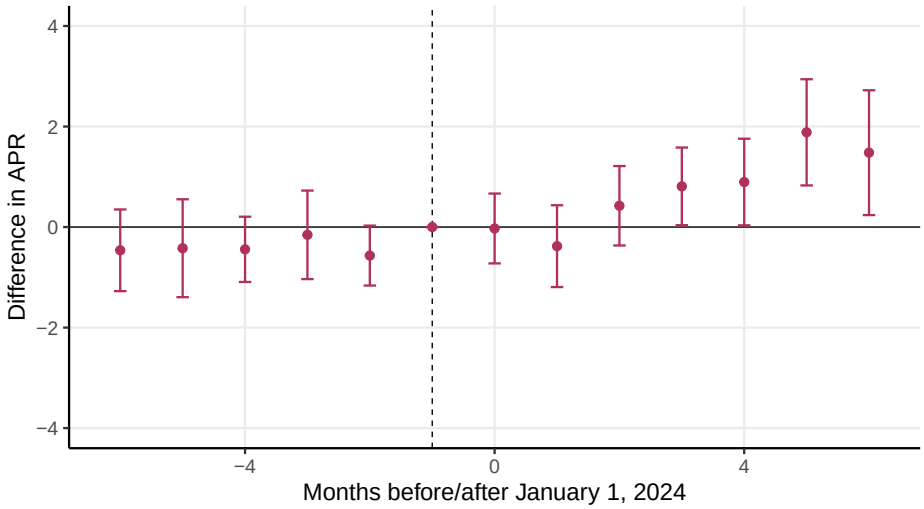
To test for policy effects on buyer income, we implement the event study specification from Appendix D.1.1 using median household income in the buyer's zip code as a proxy. If buyers sort by income around the policy event, average buyer income should decrease after implementation, as higher-income ineligible buyers purchase early to avoid potential price increases while lower-income eligible buyers delay purchases to claim the credit.

Figure A3: **APR Trends for Predicted-Eligible EVs in January 2023 and 2024**

(a) 2023



(b) 2024

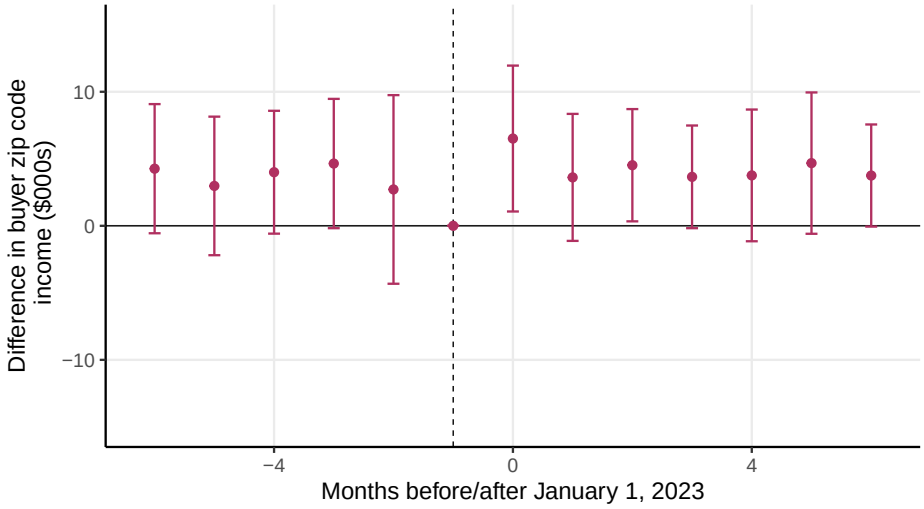


Notes: This figure presents β_1 coefficients from the event study estimator in equation (94) with APR as the outcome variable. Panels (a) and (b), respectively, present the event studies for the beginning of the tax credit in January 2023 and the availability of dealership transfer in January 2024. Whiskers indicate 95 percent confidence intervals.

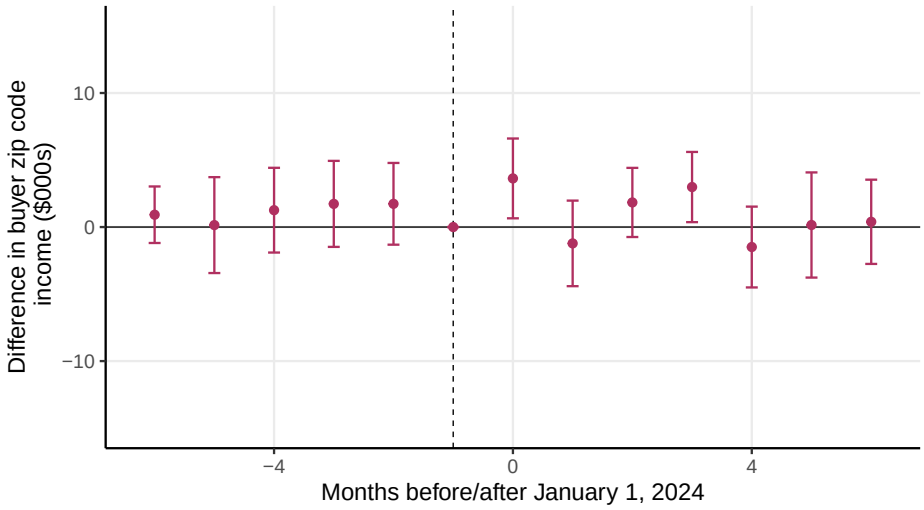
Figure A4 presents the β_1 coefficients in the income event study specifications. We find no evidence of income-based sorting around either policy event. While we observe a positive, statistically significant coefficient in period 1 for Panel (a) and Panel (b), the overall pattern is flat and the direction is opposite to

Figure A4: **Buyer Income Trends for Predicted-Eligible EVs in January 2023 and 2024**

(a) 2023



(b) 2024



Notes: This figure presents β_1 coefficients from the event study estimator in equation (94) with median zip code income as the outcome variable. 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.

what we would expect if the policy were driving buyer composition changes.

For the January 2023 policy event, the pre-post specification reported in Table A2 allows us to reject changes in average buyer income larger than $943 with 95 percent confidence. Similarly, for January 2024,

we reject changes larger than $1,338, shown in Table A3.

D.2.3 Quantity Effect

To test whether buyers time their purchases around the policy implementation, we analyze trends in transaction quantities. If eligible buyers delay purchases to claim the credit, we would expect reduced transactions for eligible EVs immediately before January 2023 and a spike at implementation.

Because the Cox data represents only a subset of the US vehicle market, we use Experian data for the quantity analysis. The Experian data contains monthly sales volumes for each vehicle type, defined as model by MY, of used vehicles sold to individuals. We limit the sample to vehicle types with MYs 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.

The quantity event study regression uses a triple-difference specification with monthly transaction quantities as the outcome variable. 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. To construct price groups for the triple-differences specification, we merge price information from the Cox data. We define the low-price group as vehicle types with greater than 50 percent of transactions below $21,000 in 2023 Q1 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.

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 q_{jyt} denote monthly transaction quantity for vehicle model j and MY y divided by the average monthly transactions from 2022. We include body type-by-month (γ_{bt}), model (γ_j), and model year (γ_y) fixed effects.

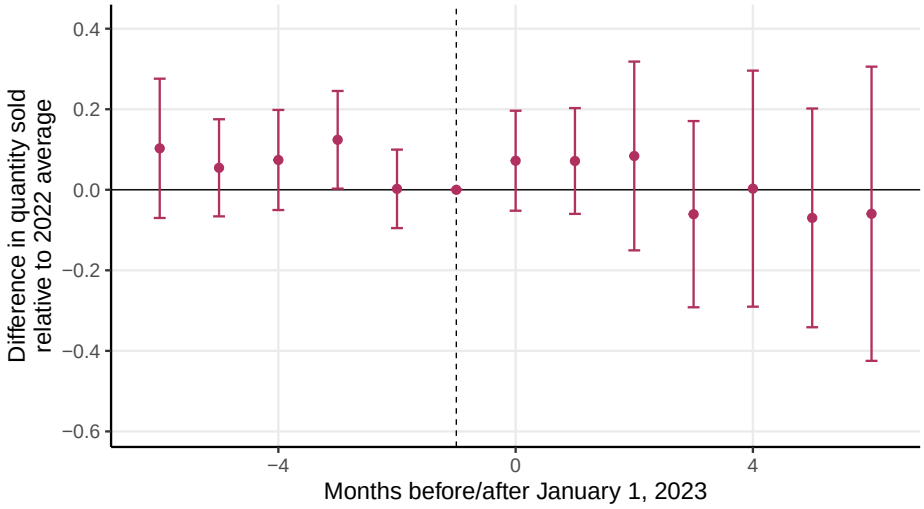
The event study regression is

$$q_{jyt} = \beta_1 A_t EV_j G_{jy} + \beta_2 A_t EV_j + \beta_3 A_t G_{jy} + \beta_4 EV_j G_{jy} + \beta_5 G_{jy} + \gamma_{bt} + \gamma_j + \gamma_y + \epsilon_{jyt}. \tag{95}$$

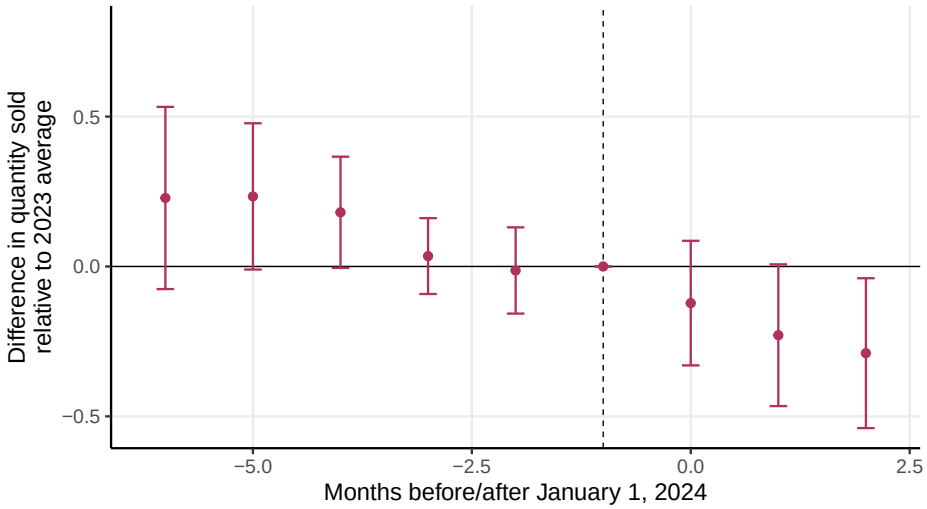
We scale transaction quantities by the 2022 monthly average to capture changes relative to a baseline level without using logs, which is necessary because many vehicle types have zero transactions in multiple months. We weight observations by the 2022 monthly average number of transactions because cheaper GVs have much higher transaction levels than other categories, and unscaled levels would be dominated by changes in this category. This specification yields estimates comparable across models regardless of their baseline transaction volumes. We cluster standard errors by vehicle type.

Figure A5: **Quantity Triple-Differences Event Study**

(a) 2023



(b) 2024



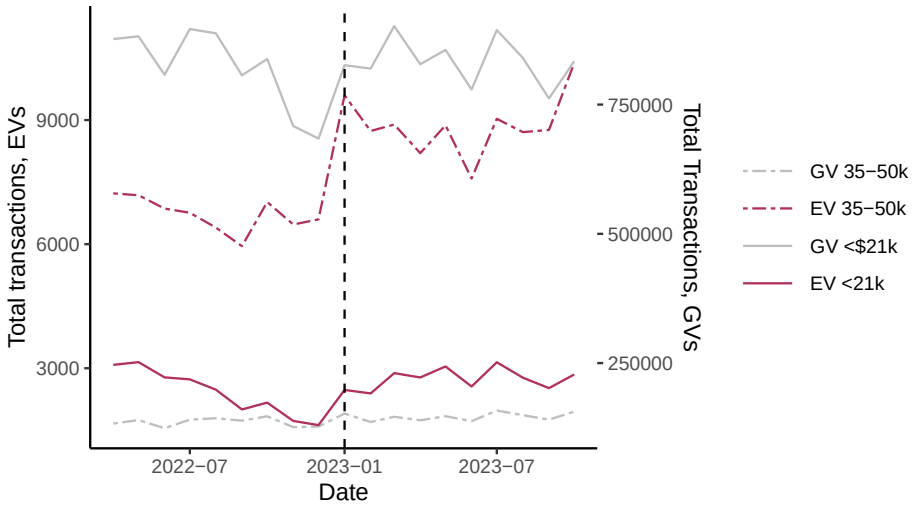
Notes: This figure presents β_1 coefficients from the event study estimator in equation (95), interpreted as the trend in transaction quantities for predicted-eligible EVs relative to predicted-ineligible EVs and GVs. Panels (a) and (b), respectively, present the event studies for the beginning of the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

Figure A5 presents the β_1 coefficients in the quantity event study specifications. Panel (a) suggests no statistically detectable changes in transaction quantities of predicted-eligible EVs after the used EV tax credit began in January 2023. The results of the corresponding pre-post specification are presented in Table

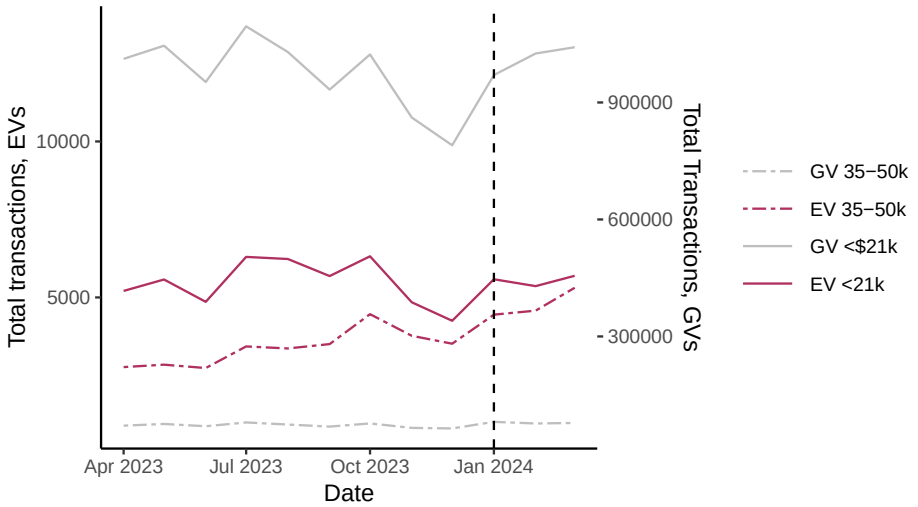
A4. Panel (b) suggests a decrease in transaction quantities of predicted-eligible EVs after the dealership transfer change in January 2024. However, this appears to follow an existing trend in the pre-period, making the event study β_1 coefficients harder to interpret.

Figure A6: **Raw Transaction Quantity by Treatment Group**

(a) 2023



(b) 2024



Notes: This figure shows the total transaction counts for each treatment group over the 2023 and 2024 event study sample periods. Treatment groups are based on fuel type and predicted price group. The left-hand y-axis shows transaction count for EVs and the right-hand y-axis shows the count for GVs.

Figure A6 shows the raw total transactions for each treatment group. The y-axis on the left shows the quantity for EVs, and the y-axis on the right is shifted down to show the quantity for GVs. We can see that the quantity for expensive EVs is increasing over time, with a jump at the start of 2023. As discussed above, this appears to be primarily driven by more recent model years entering the used vehicle market. The quantity of cheap EVs is decreasing up until the start of 2023, after which we see a modest rebound. However, we see a similar pattern for the cheap GVs, meaning that we cannot clearly identify this as a policy effect.

D.2.4 Changes in Dealership Transaction Shares

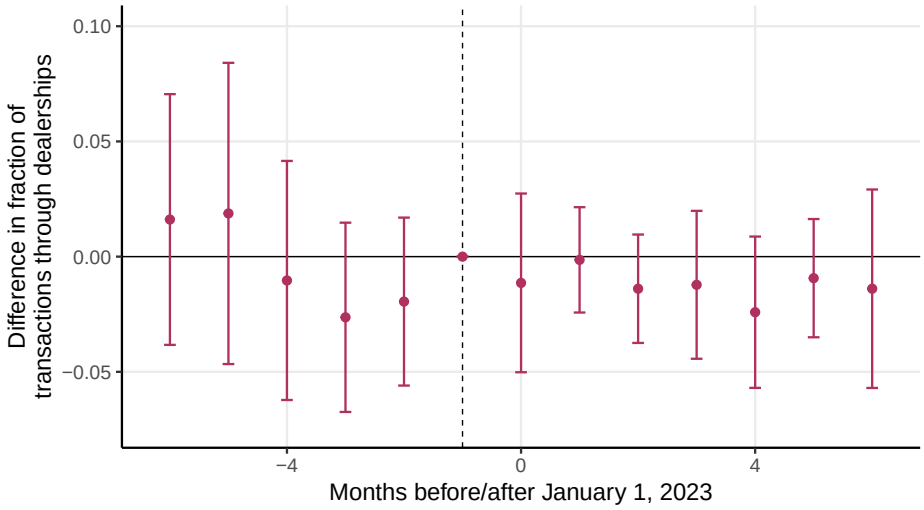
The share of eligible used EV transactions occurring through dealerships could increase following the policy implementation, since the tax credit can only be claimed through eligible dealers. This effect could also occur after the dealership transfer change in January 2024, when consumers gained the option to immediately claim the credit at the point of sale through the dealership. If dealerships capture more of the credit's value under this system and pass some benefit to sellers, the dealership share could increase. Because we find no evidence of a quantity effect in Appendix D.2.3, any increase in dealership share would likely reflect individuals shifting from private sales to dealership sales rather than additional transactions induced by the tax credit.

To test for this type of substitution in the used vehicle market, we apply the empirical strategy from Appendix D.2.3 with dealership share of transactions as the outcome variable. Figure A7 presents the β_1 coefficients in the dealership share event study specifications. Both Panel (a) and Panel (b) suggest no statistically detectable change in transaction quantities of predicted-eligible EVs after the used EV tax credit policy changes. Figure A8 shows the corresponding trends in the raw data.

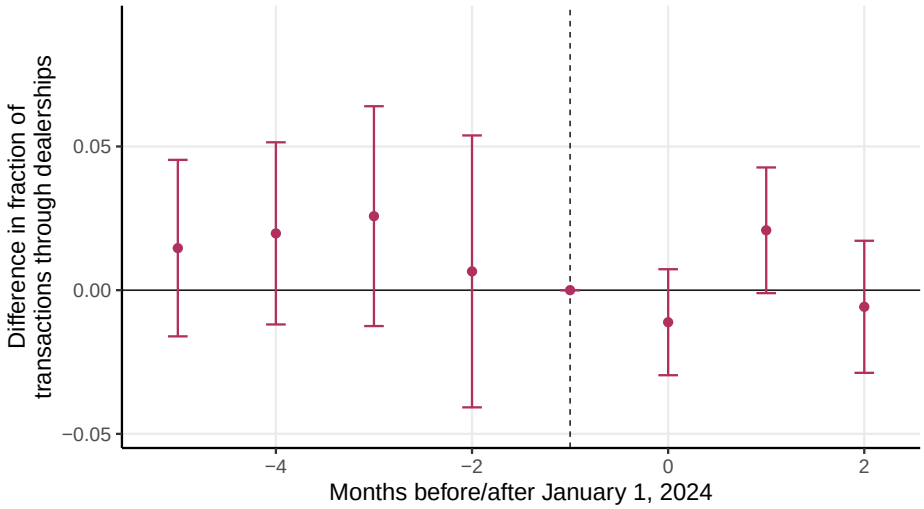
We find no evidence that the dealership share of transactions responded to either policy event. Combined with the absence of quantity effects, this suggests that individuals did not shift their selling behavior in the short run in response to the used EV tax credits. This is consistent with sellers having limited awareness of the policy or not expecting to receive additional payment from dealerships for potentially eligible vehicles.

Figure A7: **Dealership Share Triple-Differences Event Study Around January 2023**

(a) 2023

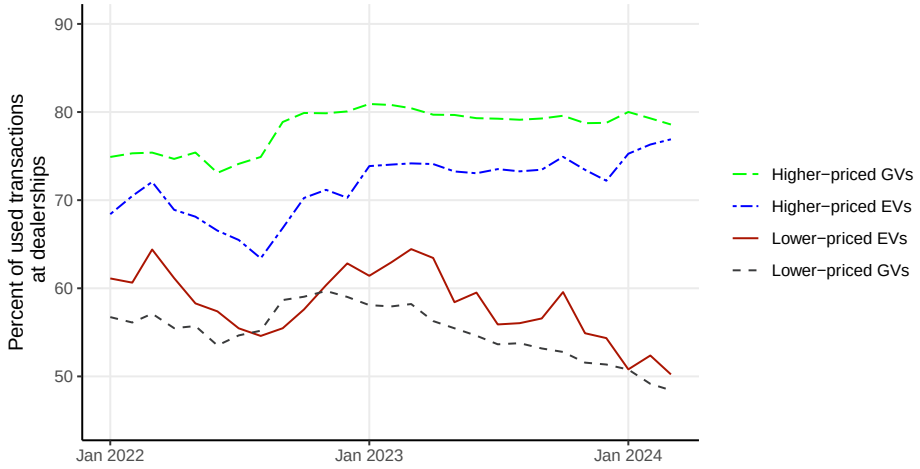


(b) 2024



Notes: This figure presents β_1 coefficients from the event study estimator in equation (95), 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.

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.

D.3 Event Study Regression Tables

This section presents the results of the price prediction regression and triple-difference analyses corresponding to our event studies.

Table A1: **Price Prediction Regression**

	(1)	(2)
	2023	2024
	ln(Transaction Price)	
ln(Odometer)	-0.1209	-0.1457
	(0.0002)	(0.0002)
Fixed effects		
Make × Month-of-Year	Yes	Yes
MY	Yes	Yes
Model	Yes	Yes
Dealership	Yes	Yes
Observations	3,741,768	3,478,094

Notes: This table shows OLS results from estimation of equation (93). An observation is a transaction.

Table A2: **Price, APR, and Buyer Income Effects around January 2023**

	(1) ln(Transaction price)	(2) APR	(3) Buyer income ($000s)
EV × predicted price <$21k	-0.031	0.406	1.174
× after Jan. 2023	(0.034)	(0.274)	(1.080)
ln(Odometer)	-0.189	1.203	-1.367
	(0.008)	(0.046)	(0.057)
Fixed-effects			
Make × Time-to-treat	Yes	Yes	Yes
MY	Yes	Yes	Yes
Model	Yes	Yes	Yes
Dealership	Yes	Yes	Yes
Observations	1,742,994	890,749	1,682,915

Notes: This table presents the results of the pre-post specification of equation (94) around the January 1, 2023 tax credit implementation. Column (1) presents the results for the price event study, Column (2) presents the results for the APR event study, and Column (3) presents the results for the buyer income event study. Buyer income is quantified as the median zip code income in units of $000s. An observation is a vehicle transaction. Standard errors are clustered at the model level.

Table A3: **Price, APR, and Buyer Income Effects around January 2024**

	(1) ln(Transaction price)	(2) APR	(3) Buyer income ($000s)
EV × predicted price <$21k	0.021	0.959	-0.031
× after Jan. 2023	(0.020)	(0.168)	(0.667)
ln(Odometer)	-0.211	1.287	-1.278
	(0.008)	(0.045)	(0.055)
Fixed-effects			
EV × predicted price <$21k	Yes		
× after Jan. 2023 Make × Time-to-treat	Yes	Yes	Yes
group_treat	Yes		
MY	Yes	Yes	Yes
Model	Yes	Yes	Yes
Dealership	Yes	Yes	Yes
Observations	1,599,117	797,824	1,471,055

Notes: This table presents the results of the pre-post specification of equation (94) around the January 1, 2024 dealership transfer change. Column (1) presents the results for the price event study, Column (2) presents the results for the APR event study, and Column (3) presents the results for the buyer income event study. Buyer income is quantified as the median zip code income in units of $000s. An observation is a vehicle transaction. Standard errors are clustered at the model level.

Table A4: **Quantity Effects around January 2023**

	(1) Scaled transaction quantity	(2) Dealership %
EV × predicted price <$21k	-0.134	-0.019
× after Jan. 2023	(0.125)	(0.015)
Fixed-effects		
Make × Time-to-treat	Yes	Yes
MY	Yes	Yes
Model	Yes	Yes
Observations	28,785	28,024

Notes: This table presents the results of the pre-post specification of equation (95) around the January 1, 2023 tax credit implementation. Column (1) presents the results of the transaction quantity event study, and Column (2) presents the results of the dealership share event study. An observation is a model-MY-month. Standard errors are clustered at the model level.

D.4 Bunching Appendix

D.4.1 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: $f_1(34) = l_1(34) + \overline{\lambda}_5 l_1(35) + \underline{\lambda}_5(33)$.

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

$$f_T(b) = \Lambda(l_T) = l_T(b) + \sum_{k\in\{5,10\}} \Bigg[\underbrace{-m_k(b+2)\cdot \underline{\lambda}_k l_T(b)}_{\text{upward shift from below}} + \underbrace{m_k(b+1)\cdot\left(\underline{\lambda}_k l_T(b-1) + \overline{\lambda}_k l_T(b+1)\right)}_{\text{excess mass}} \tag{96}$$

$$- \underbrace{m_k(b)\cdot \overline{\lambda}_k l_T(b)}_{\text{downward shift from above}} \Bigg].$$

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

$$f_1(b_n) = h(b_n) + \sum_k m_k(b_n+1)\cdot(\underline{\lambda}_k h(b_n-1) + \overline{\lambda}_k h(b_n+1)) - m_k(b_n+2)\cdot\underline{\lambda}_k h(b_n) - m_k(b_n)\cdot\overline{\lambda}_k h(b_n) \tag{97}$$

with non-linear least squares, given λ acts multiplicatively on the quadratic fit. We include all months from 2022-2025.

Table A5 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 A5 column 2.

Table A5: Λ **Left-Digit Effect Estimates**

	GVs		EVs	
	(1)	(2)	(3)	(4)
$\overline{\lambda}_5$	0.023	0.021	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

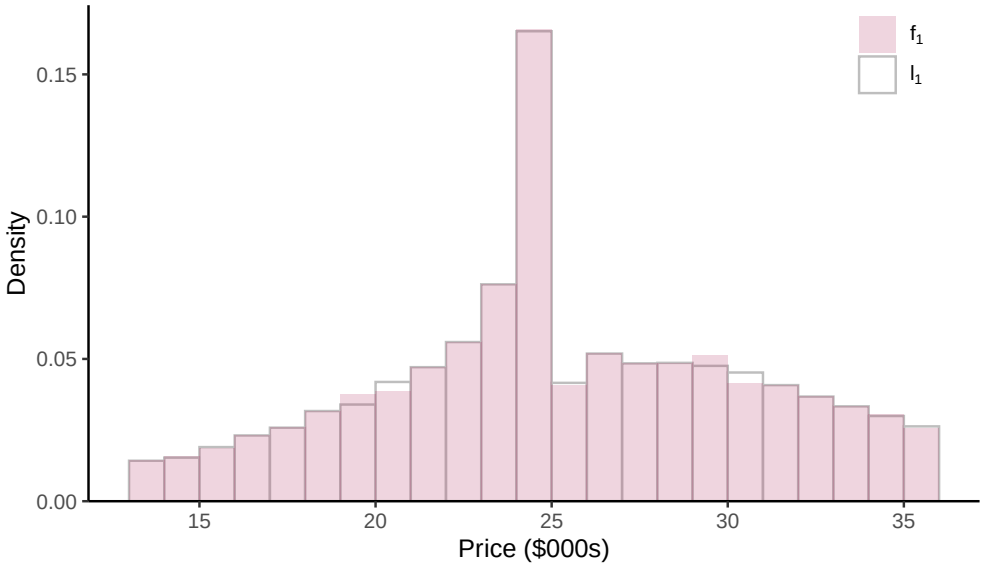
Notes: This table shows the resulting Λ values from estimating equation (97) using only GV transactions in columns 1–2 and only EV transactions in columns 3–4. We restrict $\underline{\lambda}_5 = \underline{\lambda}_{10} = 0$ in columns 2 and 4.

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 3–4 of Table A5 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 EVs are more expensive on average, thus we include central bins up to \$99,000. The EV and GV results are largely similar. In the restricted case, switching to EVs causes $\overline{\lambda}_5$ to change slightly from 0.021 to 0.017 and $\overline{\lambda}_{10}$ from 0.062 to 0.066.

We apply the estimated Λ values to our estimation of $\widehat{\rho\tau_u}$ through 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 (96). Figure A9 presents the estimated l_1 for the 2024+ distribution, showing a bit more mass just above round numbers compared to f_1.

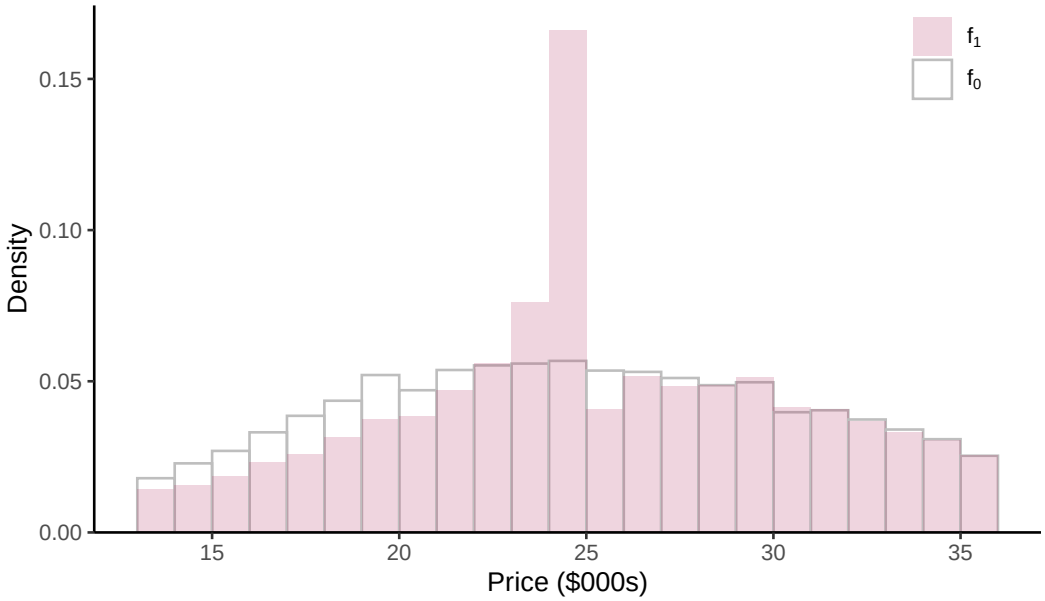
After estimating the latent counterfactual density l_0 via regression in step 2, we reconstruct the counterfactual density f_0 in step 3. To do this, we simply apply equation (96). Figure A10 plots the results of the full procedure, showing the observed price density f_1 in maroon and the predicted counterfactual 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 A9: **Equilibrium and Latent Factual Distributions**



Notes: This graph shows the EV binned latent density distribution l_1 for 2024+ after applying the Λ values from column 1 of Table A5 to the observed EV density f_1.

Figure A10: **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 using the inverse of Λ.

D.4.2 Bunching Estimation Strategy Appendix

Our standard errors on $\rho\tau_u$ reflects uncertainty in the left-digits 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. This method of bootstrapping tests the sensitivity of our results to the binning of the transactions.

One bootstrap iteration has the following steps. First, we assume Λ is distributed normal 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 $\widetilde{\rho\tau_u}$ 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.4.3 Bunching Results Appendix

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

Figure A11 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 3. 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.

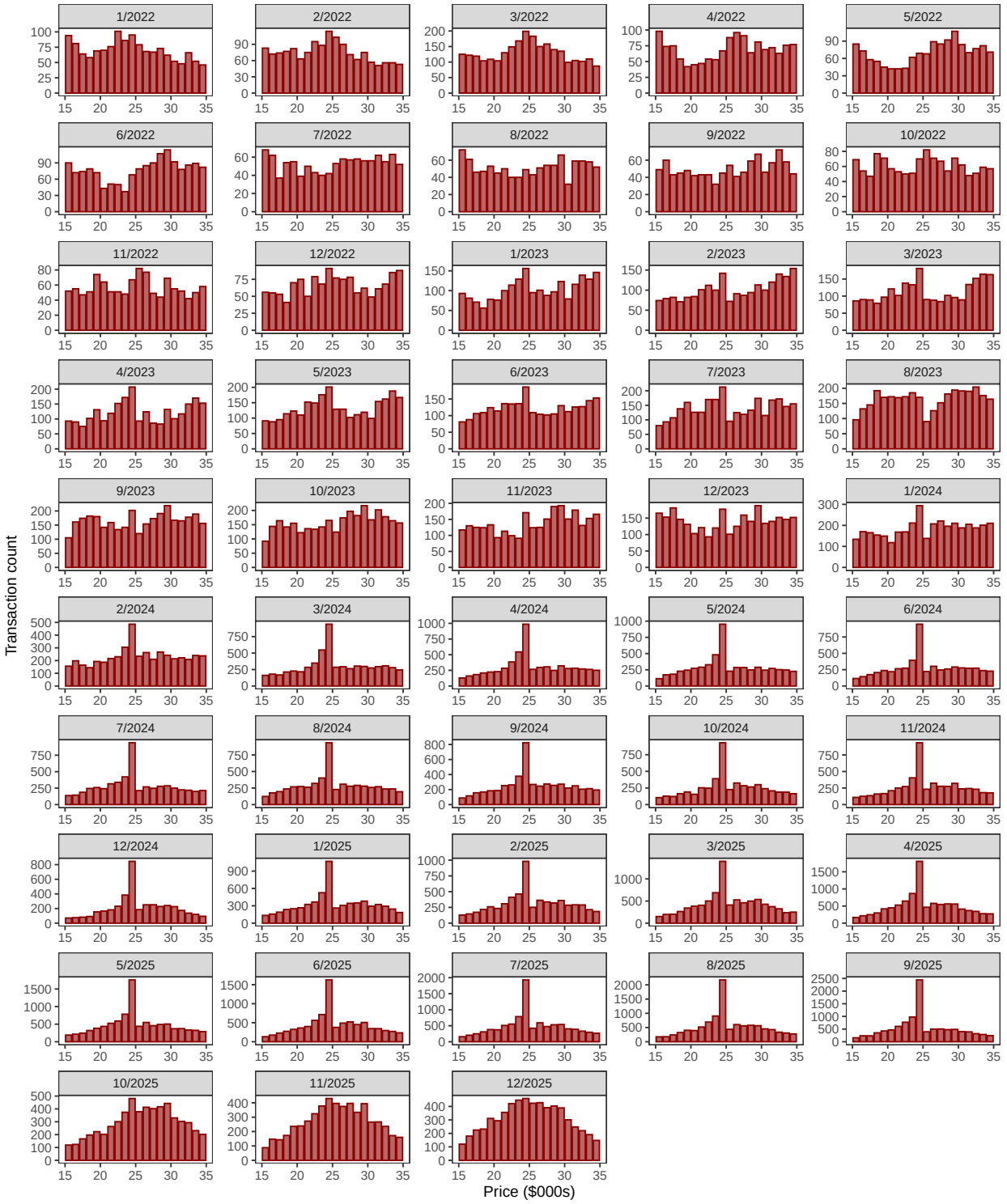
Our estimates of $\widehat{\rho\tau_u}$ in the main body use a fifth order polynomial, but our results are quite robust to alternative orders. Figure A12 shows the counterfactual fit for the 2024+ latent distribution estimated from equation (7) assuming different orders $K \in \{2, \ldots, 9\}$. The 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 A13 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.4.2. 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 A12. 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 A12, 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 A13, and it is consistent with the other polynomial fits.

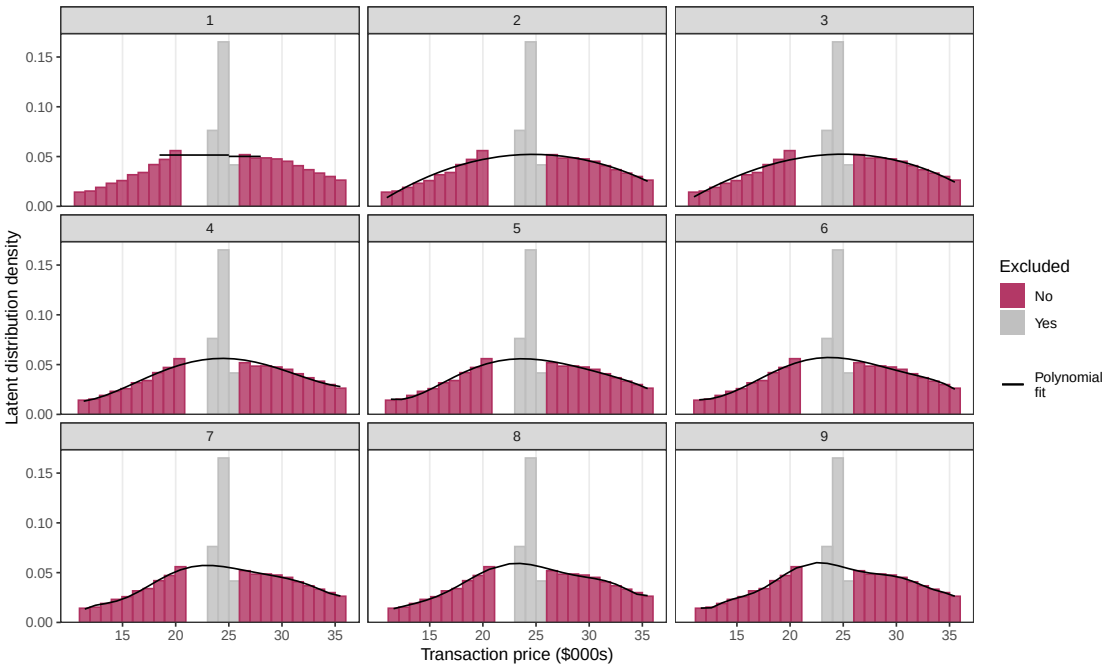
As a final robustness check, we present our results using our preferred fifth order polynomial with different assumptions regarding $\overline{p}$ and $\underline{p}$. We present the resulting $\widehat{\rho\tau_u}$ estimates for EVs for each of 2022, 2023, and 2024+ in Table A6. The results are similar to our primary specification presented in the body.

Figure A11: **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.

Figure A12: **Fitted Counterfactual of 2024+ Distribution by Polynomial Order**



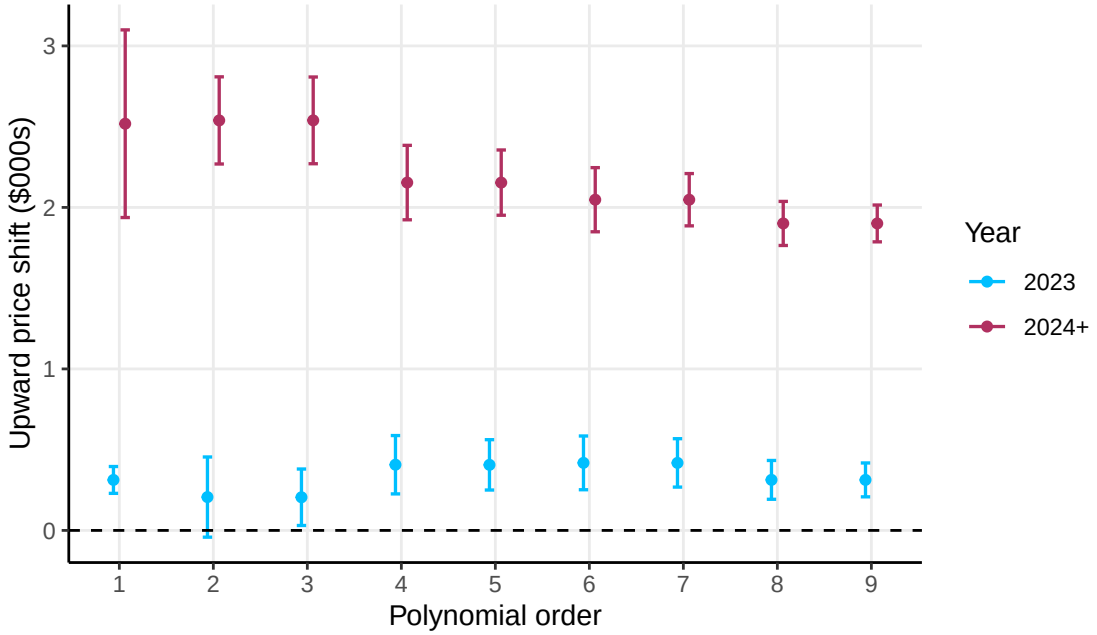
Notes: Each subplot shows the estimated counterfactual from equation (7) that solves the excess mass equation using polynomial orders 2–9. The uniform panel in the top left uses local uniformity on each side of the excluded region. Each bar represents a $1,000 bin.

Table A6: **Alternative Specifications**

	(1)	(2)	(3)
	2022	2023	2024+
$\underline{p} = \$22,001$	209	557	2,481
	(115)	(88)	(107)
$\overline{p} = \$27,000$	170	324	2,080
	(85)	(81)	(103)

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 A13: $\rho\tau_{\mathbf{u}}$ **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 (7). For polynomial order 1, we use local uniformity on each side of the excluded region, see text for details.

D.4.4 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 main body as panel (b) of Table 3. The basis of these calculations is our model of prices given in equation (5). 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 assume any left-digit bias moves the price by \$1,000. For example, if p_{i1} = \$24,500, then

$$\mathbb{P}(p_{i1}^L = \$23{,}500) = \underline{\lambda}_5 l_1(23)/D \tag{98}$$

$$\mathbb{P}(p_{i1}^L = \$24{,}500) = l_1(24)/D \tag{99}$$

$$\mathbb{P}(p_{i1}^L = \$25{,}500) = \overline{\lambda}_5 l_1(25)/D, \tag{100}$$

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_{i0} probabilistically, as described above, compute the expected value of the price shift for transaction i, and then average across transactions.

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 (5). We calculate

$$d \coloneqq \frac{\Big(F_0(26) - F_0(25)\Big) - \Big((F_1(26) - F_1(25)\Big)}{F_0(26) - F_0(25)}, \tag{101}$$

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

$$F_1(26) - F_1(25) + F_1(25) - F_1(23) = F_0(26) - F_0(25) + F_0(25) - L_0(23 - \widehat{\rho\tau_u}). \tag{102}$$

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

$$F_1(25) - F_1(23) - d[F_0(26) - F_0(25)] = F_0(25) - L_0(23 - \widehat{\rho\tau_u}). \tag{103}$$

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 compute the average price on the right-hand side, we want to use the f_0 distribution. Thus, we first compute $F_0(25) - F_0(23 - \widehat{\rho\tau_u})$ assuming bin uniformity. We then use the expected value of the f_0 price for any transactions between $F_0(23 - \widehat{\rho\tau_u}) - L_0(23 - \widehat{\rho\tau_u})$.

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 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 A7, 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 A7. 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 A7. 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 A7 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 number of eligible transactions in the data, we can get an alternative estimate of the fraction of purchasers that are income eligible. To construct the data counterpart, we have to 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 and occurred at dealerships. Second, in the Cox data we find the fraction of used sales in 2023 costing under $25,000. We join these at the level of make-model-model year and multiply the total sales by the eligible fraction to get a rough estimate of the used EV transactions that were eligible for tax credits. We find 65,964 potentially eligible transactions, which implies at most 43 percent of purchasers are income eligible, assuming perfect uptake among eligible purchasers. This is similar to the 50 percent eligibility we derived from tax data.

Table A7: **Tax Liability Statistics**

	Share of purchases < $25k				Share with tax liability				Value of $4k tax subsidy | tax liability > 0				
Income	(1) Married filing joint	(2) Married filing single	(3) Head of household	(4) Single	(5) Married filing joint	(6) Married filing single	(7) Head of household	(8) Single	(9) Married filing joint	(10) Married filing single	(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%	84.2%	84.6%	88.3%	80.3%

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 without any tax liability and then 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 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 rows uses only income eligibility and the shares in columns 1–4.

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.

$$g_{ja}(p_{jat}) = \min\left\{\exp(\eta^a a)\cdot\left(\frac{p_{jat}-v_j^s}{\psi_j}\right)^{\eta^p},\ 1\right\}. \tag{104}$$

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

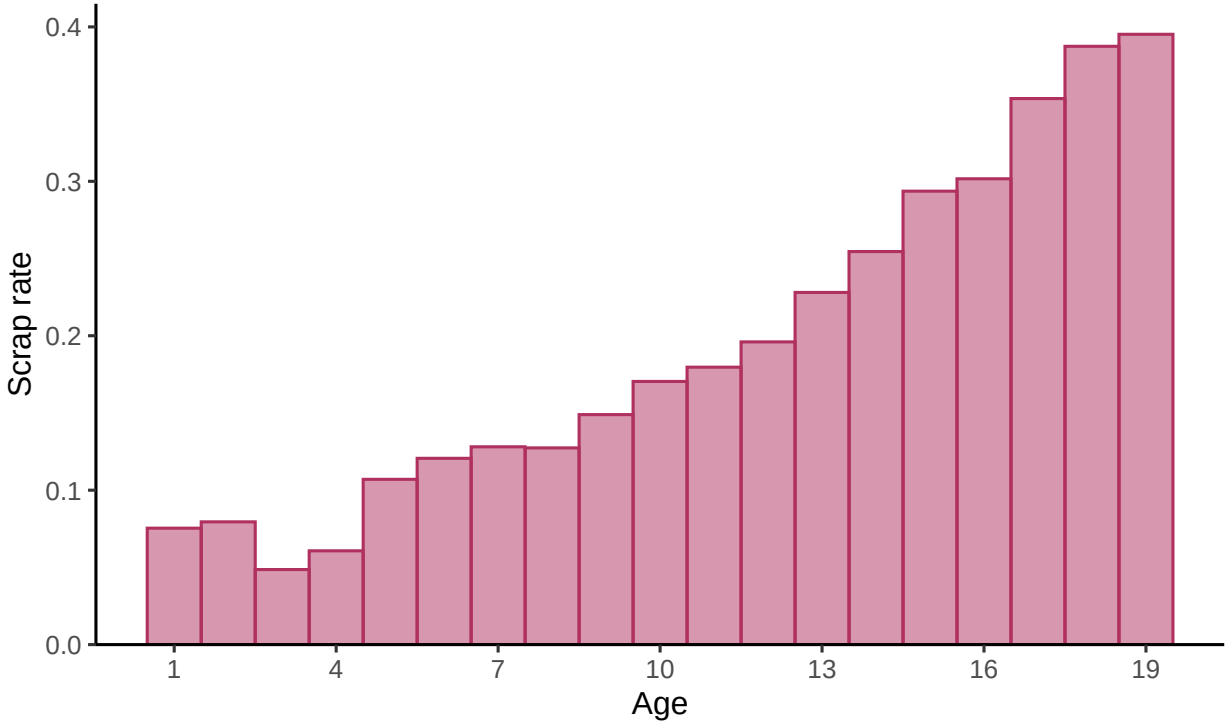
The necessary parameters for the scrappage model above are η^a (the age effect on scrappage), η^p (the price elasticity of scrappage), ψ_j (the model-specific scrap rate shifter), and r_j^s (the scrap value). As described in Section 6.1, we calibrate the scrap elasticity to -0.7 and assume scrap values $v_j^s = \$1000$ 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 (104), substitute $\gamma_j = -0.7\ln(\psi_j)$, and re-arrange, giving the following estimating equation:

$$\ln(g_{ja}) + 0.7\ln(p_{ja} - v_j^s) = \eta^a a + \gamma_j + \epsilon_{ja}. \tag{105}$$

Figure A14 presents the average scrap rate by age. Table A8 presents the estimates of equation (105). 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 (105), we winsorize the car type fixed effects ψ_j at the 10th and 90th percentile for use in the structural model.

Figure A14: **Average Scrap Rate by Age**



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

Table A8: **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 (105). 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 Appendix

E.2.1 Expected Resale Values

Given isoelastic scrappage as characterized in equation (104), a vehicle's expected resale value in all ages $a \leq 19$ is

$$\tilde{v}_{jat}(\tilde{p}_{jat}) = g_{ja}(\tilde{p}_{jat}) \cdot v_j^s + (1 - g_{ja}(\tilde{p}_{jat})) \cdot \tilde{p}_{jat} - \psi_j \int_{\exp(\eta_a a)^{-\frac{1}{\eta_p}}}^{\frac{\tilde{p}_{jat} - v_j^s}{\psi_j}} x \, dG(x). \tag{106}$$

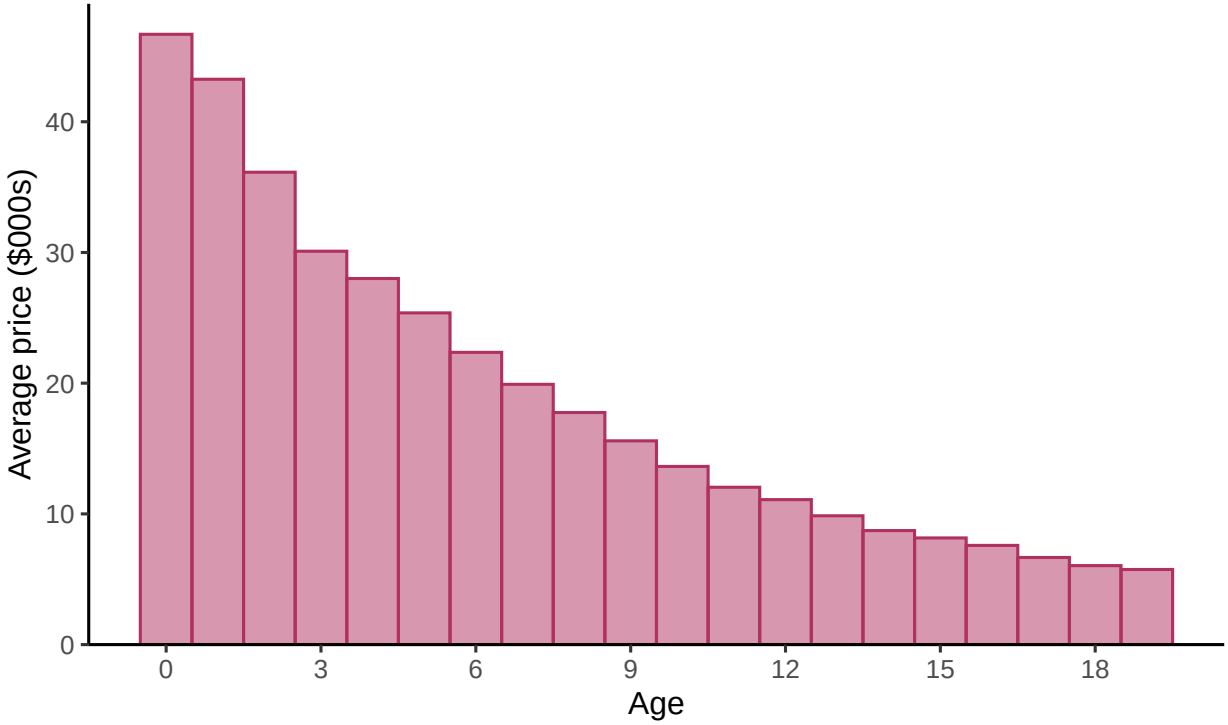
As in Section 3, tildes on p and v indicate that these are consumers' expectations of future values. For vehicles aged $a \geq 20$, which we assume are always scrapped at the end of their holding periods, the scrap rate is $g_{ja} = 1$, and the expected resale value is just $\tilde{v}_{jat} = v_j^s$.

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:

$$\ln(p_{ja}) = \beta^n \mathbb{1}(a = 0) + \beta^a a + \gamma_j + \epsilon_{ja}. \tag{107}$$

Figure A15 presents the average price by age. Table A9 presents the estimates of equation (106). We estimate $\beta^a \approx -0.11$, meaning that vehicles depreciate by about 11 percent per year. For the demand estimation, we assume that consumers' expectations $\tilde{p}_{jat}$ for prices of each model and age equal the fitted values in all future t. We then construct resale value expectations $\tilde{v}_{jat}(\tilde{p}_{jat})$ by inserting those fitted values into equation (106).

Figure A15: **Average Price by Age**



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

Table A9: **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 (107). An observation is a car type by age.

E.2.2 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 $\forall h \in \{1, \ldots, 30\}$,

$$\Gamma^{NHTS}(h) = \sum_{k=h}^{30} \frac{\Gamma^O(k)}{k}. \tag{108}$$

Due to our holding time cap at 30 years, the system of equations given in equation (108) is equivalent to recursively solving

$$\Gamma^O(h) = h \cdot (\Gamma^{NHTS}(h) - \Gamma^{NHTS}(h+1)). \tag{109}$$

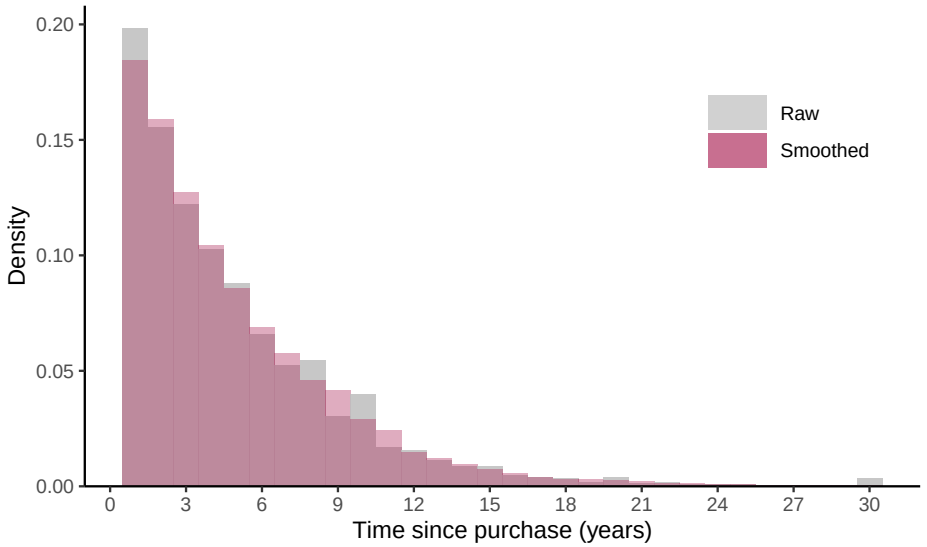
Therefore, if $\Gamma^{NHTS}(h+1) > \Gamma^{NHTS}(h)$, then $\Gamma^O(h) < 0$. Thus, we force weak monotonicity on Γ^{NHTS}. The raw distribution of Γ^{NHTS} and the smoothed version are shown in panel (a) of Figure A16.

The computed distribution of Γ^O, shown as grey bars in Panel (b) of Figure A16, is unrealistically bumpy. We perform smoothing parametrically by fitting a skew normal distribution, shown in maroon in Panel (b) of Figure A16. 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.

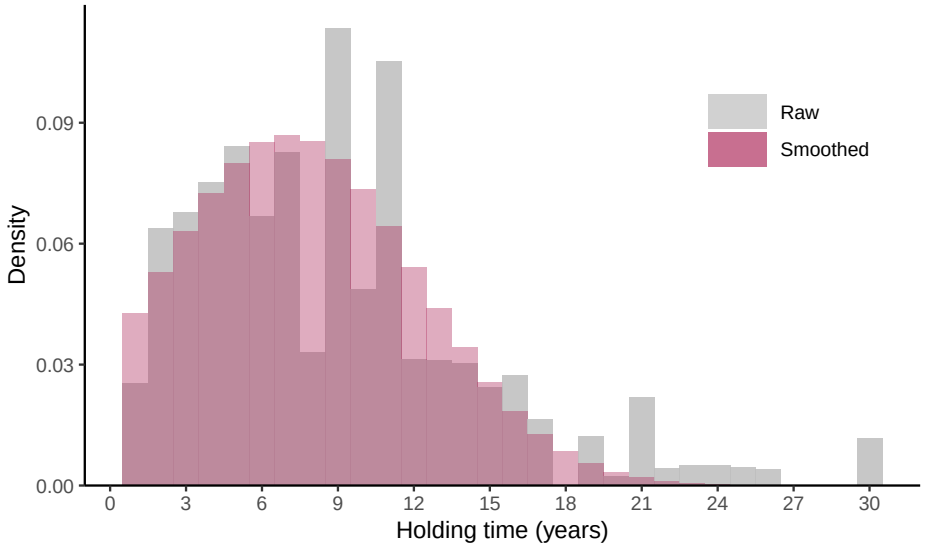
To convert from the holding time distribution of vehicle owners, Γ^O, to the holding time distribution of vehicle buyers, Γ, we need to adjust for how often each vehicle owner will enter the vehicle market. For example, an owner with holding time one will enter 20 times more often than an owner of holding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

Figure A16: **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 (108), 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.2.3 Estimator and Moment Conditions

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

$$\hat{\boldsymbol{\Theta}} = \arg\min \boldsymbol{M}(\Theta)\boldsymbol{M}(\Theta)', \quad s.t.\ q_{jy} = \sum_i Pr_{ijy}(\boldsymbol{\Theta}). \tag{110}$$

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

$$M^p(\boldsymbol{\Theta}) = \frac{1}{5}\sum_{f\in\mathcal{F}} \frac{dD^f_{2023}}{dp^f_{2023}} \frac{p^f_{2023}}{D^f_{2023}} - (-4.69). \tag{111}$$

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: $x \in \{\mathbb{1}(a+h=0), (a+h)\}$. For each variable, these moment conditions set to zero the covariance between that variable and ξ:

$$M^X(\boldsymbol{\Theta}) = \sum_j \sum_y x_{ja}\xi_{ja}. \tag{112}$$

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: $x \in \{EV_j, \mathbb{1}(a+h=0), (a+h)\}$. 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

$$M^{inc}(\boldsymbol{\Theta}) = \frac{1}{N\cdot(1-\mu_{inc})} \sum_{i|inc_i>\$150k} \sum_j \sum_y Pr_{ijy}x_{jy} - \hat{x}^{inc}. \tag{113}$$

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 three of these moments, one for each of the three vehicle characteristics x.

For the EV characteristic, $x_j = EV_j$, we match the share of consumers whose second choice is an EV (of any age), among those who bought a new EV. This matches the construction of the NVES survey, which elicits second choices (in principle, of any age) among new vehicle buyers. Define $Pr^{(2)}_{ijy|k}$ as the simulated second choice probability: the probability that consumer i chooses car type j as a second choice conditional on choosing car type k as a first choice. Further define $\hat{x}^{(2)}$ as the observed second choice share. The moment condition is

$$M^{12,EV} = \frac{\sum_i \sum_{j,y=2023|x_j=1} Pr_{ijy} \left(\sum_{j' \neq j | x_{j'}=1} Pr^{(2)}_{ij'y|j} \right)}{\sum_i \sum_{j,y=2023|x_j=1} Pr_{ijy}} - \hat{x}^{(2)}. \tag{114}$$

For the new vehicle characteristic, $x = \mathbb{1}(a + h = 0)$, the moment condition is analogous: we match the share of households whose second vehicle is new, among those whose first vehicle is new. There is one conceptual difference: the empirical moment uses 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. Since a household can own two of the same vehicle, we don't exclude j from the sum in the numerator. The moment condition is

$$M^{12,new} = \frac{\sum_i \sum_{j,y|x_{jy}=1} Pr_{ijy} \left(\sum_{j',y'|x_{j'y'}=1} Pr_{ij'y'} \right)}{\sum_i \sum_{jy|x_{jy}=1} Pr_{ijy}} - \hat{x}^{(2)}. \tag{115}$$

For the age characteristic, $x = a + h$, we match the correlation coefficient between two vehicles owned by the same household. 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

$$M^{12,age}(\boldsymbol{\Theta}) = \frac{E[x_1 x_2 \mid y_1 \neq 2023] - E[x_1 \mid y_1 \neq 2023]\ E[x_2 \mid y_1 \neq 2023]}{\sqrt{\mathrm{Var}(x_1 \mid y_1 \neq 2023)\,\mathrm{Var}(x_2 \mid y_1 \neq 2023)}} - \hat{\rho}^x, \tag{116}$$

Table A10 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 A11 presents the parameter estimates. Table A12 presents the Andrews, Gentzkow, and Shapiro (2017) sensitivity matrix, while Table A13 presents the sensitivity matrix transformed into elasticity units.

Table A15 presents the demand parameter estimates for an alternative estimate where we multiply the new vehicle second choice share empirical moment by 1/2. This is intended to increase the substitutability

between new and used vehicles. Indeed, the new vehicle random coefficient σ^{new} attenuates substantially, and the elasticities reported in Table A16 show that aggregate new vehicle demand is substantially more elastic.

Table A10: **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	0.150	(0.002)
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 second choice share	0.676	(0.008)
New vehicle second choice share	0.926	(0.060)
Correlation between vehicle ages	0.431	(0.012)

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

Table A11: **Demand Parameter Estimates**

Parameter	Description	(1) Estimate	(2) Standard error
α_0^p	Price response	2.506	0.619
α_0^{new}	New demand intercept	3.012	0.403
α_0^{age}	Age demand intercept	-0.005	0.026
α_{inc}^{EV}	High-income EV demand shifter	10.202	1.115
α_{inc}^{new}	High-income new demand shifter	6.184	1.181
α_{inc}^{age}	High-income age demand shifter	0.016	0.013
σ^{EV}	EV random coefficient	14.335	1.549
σ^{new}	New random coefficient	1.036	0.268
σ^{age}	Age random coefficient	-0.065	0.005

Notes: This table presents the demand parameter estimates.

Table A12: **Sensitivity Matrix**

	New price elasticity	High-income EV share	High-income new share	High-income avg. age	EV second choice share	New second choice share	Age correlation	$\sum$ 1(new) * ξ	$\sum$ Age * ξ
α_0^p	-0.616	-0.736	1.378	-0.005	-0.206	7.051	0.158	4.057	0.060
α_{inc}^{EV}	-0.206	166.432	17.678	0.318	96.304	-61.817	-0.224	3.702	0.018
α_{inc}^{new}	0.007	-16.168	30.481	2.672	1.354	-9.235	-2.473	-85.427	-1.254
α_{inc}^{age}	-0.006	0.040	0.015	0.106	-0.004	0.083	-0.039	-0.031	-0.000
σ^{EV}	0.418	6.111	-20.682	0.017	152.185	-110.635	-0.709	-33.221	-0.493
σ^{new}	-0.246	3.948	2.501	-0.177	-2.840	67.792	0.929	73.931	1.086
σ^{age}	-0.002	0.007	0.018	-0.012	0.004	0.191	-0.287	0.128	0.002
α_0^{new}	0.007	-7.431	-10.186	-0.073	4.295	-81.653	-1.750	-127.639	-1.874
α_0^{age}	0.026	-0.015	-0.097	-0.011	0.013	-0.487	0.266	-0.765	-0.050

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

Table A13: **Sensitivity Matrix in Elasticity Units**

	New price elasticity	High-income EV share	High-income new share	High-income avg. age	EV second choice share	New second choice share	Age correlation	$\sum$ 1(new) * ξ	$\sum$ Age * ξ
α_0^p	1.123	-0.039	0.281	0.000	-0.059	2.349	0.028	-0.115	0.002
α_{inc}^{EV}	0.092	2.177	0.886	-0.003	6.739	-5.058	-0.010	-0.026	0.000
α_{inc}^{new}	-0.005	-0.349	2.521	-0.038	0.156	-1.246	-0.178	0.982	-0.019
α_{inc}^{age}	1.713	0.334	0.480	-0.586	-0.178	4.331	-1.085	0.138	0.000
σ^{EV}	-0.133	0.057	-0.738	0.000	7.579	-6.443	-0.022	0.165	-0.003
σ^{new}	1.085	0.508	1.235	0.015	-1.957	54.612	0.399	-5.070	0.098
σ^{age}	-0.141	-0.014	-0.142	-0.016	-0.044	-2.461	1.972	0.140	-0.003
α_0^{new}	-0.011	-0.329	-1.730	0.002	1.018	-22.629	-0.259	3.011	-0.058
α_0^{age}	21.801	0.367	9.107	-0.179	-1.703	74.612	-21.731	-9.978	0.857

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 A14: **Parameter Estimates with Alternative Values of the Pure Characteristics Coefficient**

Parameter	Description	(1) $\mu_\epsilon = 3$	(2) $\mu_\epsilon = 5$	(3) $\mu_\epsilon = 7$
α_0^p	Price response	2.582	2.506	2.554
		(0.621)	(0.619)	(0.690)
α_0^{new}	New demand intercept	4.964	3.012	2.283
		(1.508)	(0.402)	(0.387)
α_0^{age}	Age demand intercept	0.036	-0.005	-0.021
		(0.028)	(0.026)	(0.028)
α_{inc}^{EV}	High-income EV demand shifter	5.456	10.202	10.760
		(0.661)	(1.115)	(2.295)
α_{inc}^{new}	High-income new demand shifter	5.862	6.184	5.856
		(1.333)	(1.181)	(1.191)
α_{inc}^{age}	High-income age demand shifter	0.011	0.016	0.019
		(0.019)	(0.013)	(0.010)
σ^{EV}	EV random coefficient	11.096	14.335	16.773
		(1.439)	(1.549)	(2.201)
σ^{new}	New random coefficient	0.827	1.036	1.817
		(0.996)	(0.268)	(0.522)
σ^{age}	Age random coefficient	-0.102	-0.065	-0.047
		(0.007)	(0.005)	(0.004)
Aggregate new vehicle price elasticity		-1.24	-1.46	-1.46
New car type $\rightarrow$ used ages average diversion ratio		0.13	0.18	0.17
Age 7 car type $\rightarrow$ other used ages average diversion ratio		0.61	0.75	0.82

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

Table A15: **Demand Parameter Estimates: Alternative Demand Specification**

Parameter	Description	(1) Estimate	(2) Standard error
α_0^p	Price response	1.774	0.370
α_0^{new}	New demand intercept	0.163	0.661
α_0^{age}	Age demand intercept	-0.143	0.016
α_{inc}^{EV}	High-income EV demand shifter	28.393	8.900
α_{inc}^{new}	High-income new demand shifter	0.625	0.188
α_{inc}^{age}	High-income age demand shifter	-0.005	0.012
σ^{EV}	EV random coefficient	23.417	11.883
σ^{new}	New random coefficient	-0.208	0.347
σ^{age}	Age random coefficient	0.029	0.002

Notes: This table presents the demand parameter estimates for an alternative estimate where we multiply the new vehicle second choice share empirical moment by 1/2.

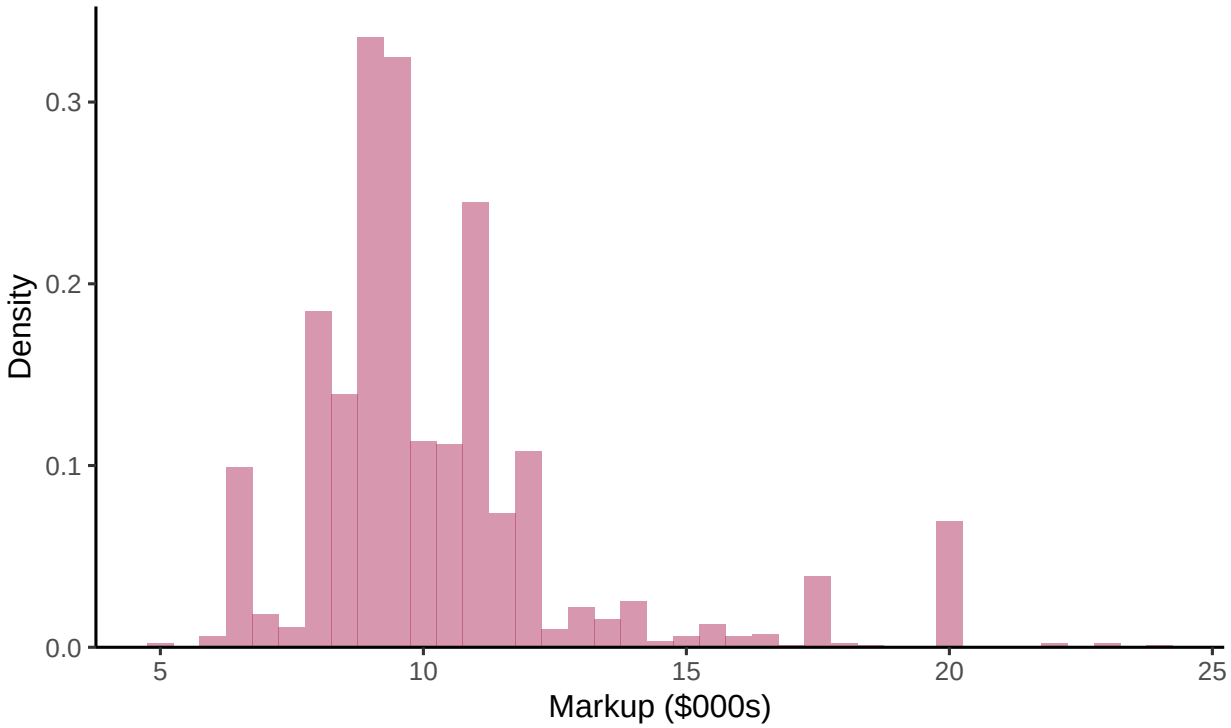
Table A16: **Selected Elasticities: Alternative Demand Specification**

Parameter	Estimate
Average new car type price elasticity	-4.78
Average firm-level price elasticity (Ford, GM, Toyota, Volkswagen, Hyundai)	-4.51
Aggregate new vehicle price elasticity	-1.51
Aggregate new EV price elasticity	-1.04
Aggregate (new+old) EV price elasticity	-0.45
New EV $\rightarrow$ new GV diversion ratio	0.39
New EV $\rightarrow$ used EV diversion ratio	0.37
Used EV $\rightarrow$ used GV diversion ratio	0.17
Used EV $\rightarrow$ new EV diversion ratio	0.37
New car type $\rightarrow$ used ages average diversion ratio	0.17
Age 7 car type $\rightarrow$ other used ages average diversion ratio	0.60

Notes: This table presents key elasticities implied by an alternative estimate where we multiply the new vehicle second choice share empirical moment by 1/2. When taking averages across car types and ages, we weight by market shares.

E.3 Marginal Cost Estimation

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.

E.4 Fleet Sales

This appendix describes how we compute fleet sales S_{jat}^{fleet} for the used vehicle market clearing equations in Section 6.4. While we assume new sales to fleets are exogenous and fixed across simulation years, existing fleet stock idiosyncrasies and model entry imply that S_{jat}^{fleet} 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_{jat}^{fleet} and Q_{jat}^{ind} 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 $g_{ja}^{all} = q_{ja,2023}^{s}/Q_{ja,2022}$, where $q_{ja,2023}^{s}$ is the total observed scrappage. We then regress annual scrap rates on class and age fixed effects, using the fitted values $\hat{g}_{ja}^{all}$ as fleet scrap rates and winsorizing at 0.

For fleet sales, we compute 2023 fleet sales $q_{ja,2023}^{fleet}$ 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:

$$q_{ja,2023}^{fleet} = Q_{ja,2023}^{ind} - Q_{ja,2022}^{ind} + q_{ja,2023}^{s} \cdot Q_{ja,2022}^{ind}/Q_{ja,2022} - D_{j,a=0,2023}, \tag{117}$$

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

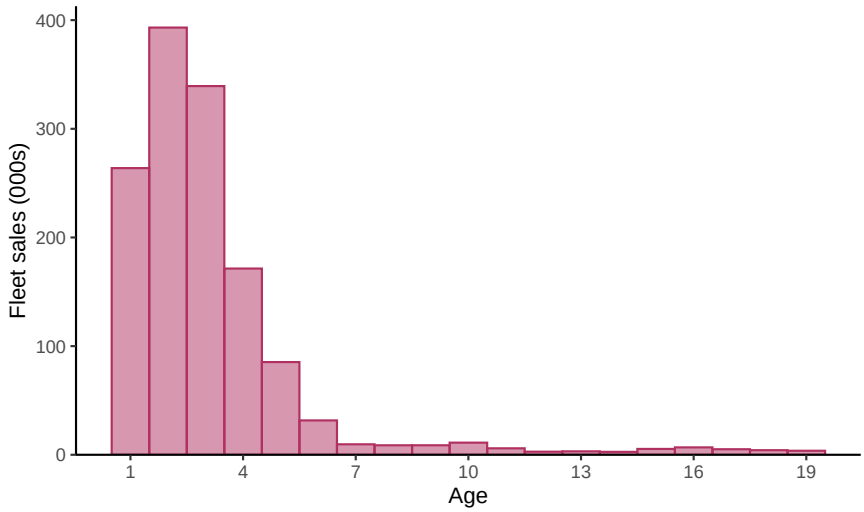
We define a fleet sales rate $q_{ja}^{fleet,r} := q_{ja,2023}^{fleet}/Q_{ja,2022}^{fleet}$ and regress $q_{ja}^{fleet,r}$ on class and age fixed effects. For each year, we then construct $S_{jat}^{fleet} := \widehat{q}_{ja}^{fleet,r} \cdot Q_{j,a-1,t-1}^{fleet}$.

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 $Q_{j,a=0,t}^{fleet}$ 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 $\widehat{g}_{ja}^{all}$ being scrapped and S_{jat}^{fleet} vehicles being sold to individuals. For $a > 1$, our yearly stock transition is $Q_{jat}^{fleet} = (1 - \widehat{g}_{ja}^{all}) \cdot Q_{j,a-1,t-1}^{fleet} - S_{jat}^{fleet}$.

Figure A18 presents the resulting sum of $S_{ja,2023}^{fleet}$ 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 A18: **Fleet Sales by Vehicle Age**



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

E.5 2023 Vehicle Ownership by Remaining Holding Time

This subsection describes how we construct $D^h_{ja,t-h}$ for years $t-h < 2023$ in Section 6.4, 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

$$\Omega^{2023}_{ja'}(z) := \sum_{k=0}^{a'} D^{h=z+a'-k}_{j,a=k,t=2023-a'+k} = \sum_{k=0}^{a'} D^{h=z+a'-k}_{j,a=k,t=2023}, \ \forall\, 0 \leq a' \leq 19, \ 1 \leq z \leq 20-a', \tag{118}$$

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:

$$\sum_{z=1}^{20} \Omega^{2023}_{ja}(z) = Q^{ind}_{ja,2023}\ , \ \forall\, 0 \leq a \leq 19. \tag{119}$$

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

$$D^h_{ja,t-h} = \frac{Q^{ind}_{ja,2023}}{\sum_{z=1}^{20} \Omega^{2023}_{ja}(z)} \cdot D^h_{ja,2023}. \tag{120}$$

While $D^h_{ja,t-h}$ is sufficient input for the simulation, in order to quantity the "windfall" welfare effects by individual (as described in Appendix E.7), we need a measure of the vehicles ending their holding period by individual, which we define as S_{ijat}.

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 $t < 2023$. The vehicles supplied to the market, or scrapped, in year t of our simulation by consumer i that were purchased before $t = 1$ are then

$$S_{ijat} = \sum_{k=t}^{H_i} \frac{Q^{ind}_{ja,2023}}{\sum_{z=1}^{20} \Omega^{2023}_{ja}(z)} \cdot Pr_{ij,a-k,2023}, \tag{121}$$

where the Q/Ω term, which is identical to that in equation (120), serves to scale the estimated demand value to match the observed 2023 vehicle stock.

E.6 Equilibrium Simulation Appendix

As described in Section 6.5, the equilibrium is a vector of prices and eligibility premia $\{\boldsymbol{p}_t, \boldsymbol{p}^e_t\}$ for all years t such that consumers correctly forecast new and used vehicle prices, firms maximize profits, and used vehicle

markets clear. We solve for the annual (non-stationary) equilibria in each year $t \in \{2023, 2024, ..., 2042\}$. For all years $t \geq 2043$, 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 their 2042 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 $t \geq 2043$ will take these steady-state values $\boldsymbol{p}_{ss}$.

The second part of the solution algorithm is to find 2023–2042 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 $t = \{2023, 2024, ..., 2042\}$:
   (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.7 Surplus 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

$$CS_{it} = \frac{H_i}{\alpha_i^p} \ln \left(\sum_j \exp(L_{ijt}) \right) + C_{i0}, \tag{122}$$

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.5 describes how we compute S_{ijat}. The "windfall" in year t for individual i is

$$\Delta v_{it} = \sum_{ja} S_{ijat} \cdot \left(v_{jat}(p_{jat} + p^e_{jat}) - v^0_{jat}(p^0_{jat}) \right), \tag{123}$$

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.

There are also sales by fleets S^{fleet}_{jat} that will receive a windfall from unexpected subsidies. Since fleets only purchase vehicles new, fleet sales S^{fleet}_{jat} only have a windfall value if $a \geq t$ (i.e. they were purchased before the simulation began). The windfall to fleets is then

$$\Delta v^{fleet}_t = \sum_j \sum_{a \geq t} S^{fleet}_{jat} \cdot \left(v_{jat}(p_{jat} + p^e_{jat}) - v^0_{jat}(p^0_{jat}) \right) \tag{124}$$

Profits earned in year t are the sum across firms of π_{ft} from equation (11).

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

$$E_t = \sum_i Pr_{ijyt} \cdot \left(\mathbb{1}(y = t) \cdot \phi^0_j + H_i \cdot \phi_{jy} \right), \tag{125}$$

where ϕ^0_j 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.8.

Total government spending on tax credits in year t is just the sum over vehicles of eligible consumers' quantity demanded times the tax credit:

$$G_t = \sum_{jy} D^e_{jyt} \cdot \tau_{jyt}. \tag{126}$$

The sum of total surplus over time is the sum of those five terms:

$$W = \sum_{t=\underline{t}}^{T} \left[\sum_i (CS_{it} + \Delta v_{it}) + \Delta v^{fleet}_t + \left(\sum_f \pi_{ft} \right) - E_t - G_t \right]. \tag{127}$$

For our steady state 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 $T = 2042$, ignoring any possible changes after 2042.

E.8 Externality Calculation

This appendix provides additional details on how we compute externalities. Table A17 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, plug-in hybrid. We assume that the externality for hybrids is the average of plug-in hybrids and gas-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).[12] 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 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 A17 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

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

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 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 A17, the extra weight profile of PHEVs and EVs yields a larger accident externality.

Positive Fiscal 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 A17 shows that fiscal externalities are larger for electricity fueled vehicles.

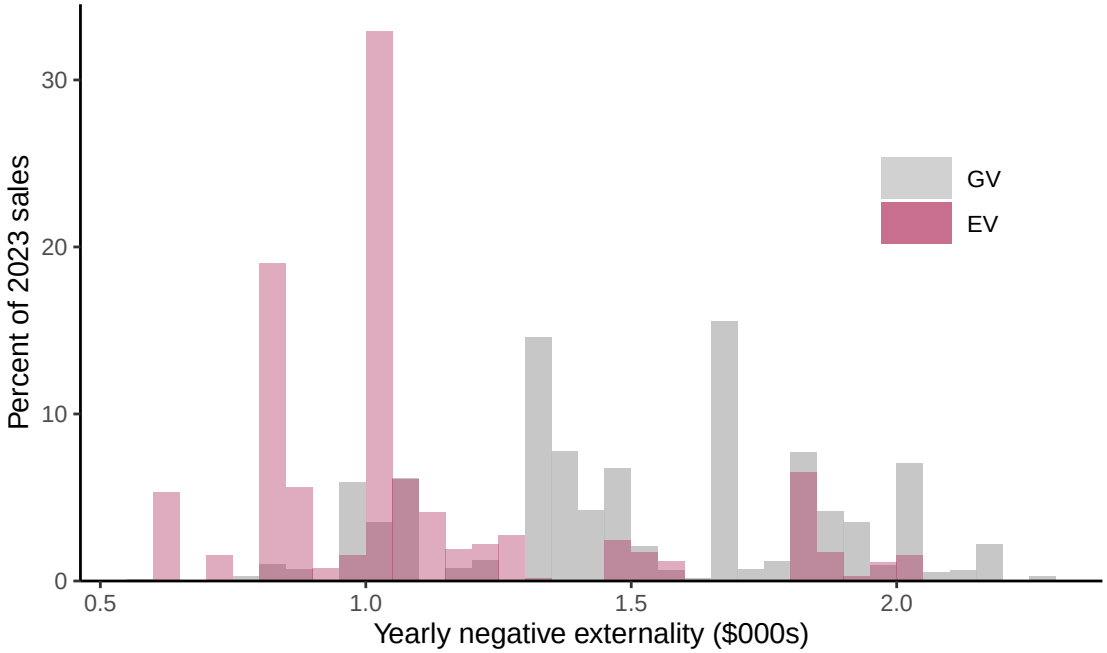
While the U.S. and other countries provide uniform subsidies for electric vehicles, there is substantial variation in externalities *within* powertrains. There is thus significant overlap in the distributions of externalities for EVs versus GVs, as shown in Figure A19. For EVs, the 10th and 90th percentiles 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 A17: **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	1,011	1,516	1,215	1,551
Driving local pollutants	36	38	19	28
Driving CO2	390	804	608	1,021
Excess weight in accidents	963	1,060	746	766
Positive fiscal externality	377	386	157	265
Expected lifetime externality	19,426	27,140	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 A19: **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).

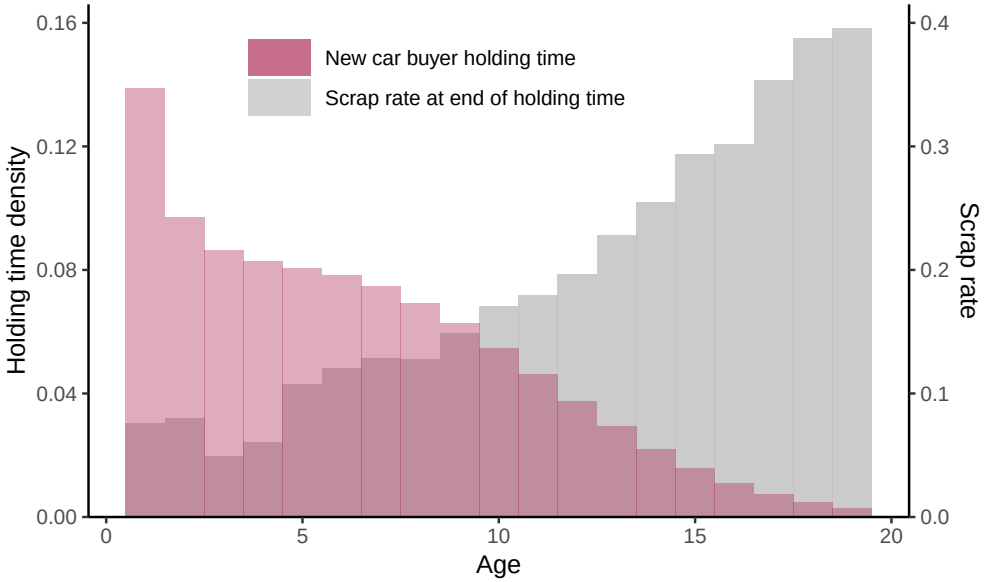
F Counterfactual Simulation Appendix

F.1 Alternative Age Eligibility Rules

This subsection presents steady state equilibrium effects when specifying that used EV transactions are only eligible for the tax credit once they have reached 10 years old. To motivate this, consider Figure A20, which shows the new car buyer holding time in maroon and the scrap rate at the end of holding time in gray. Roughly 75 percent of new car buyers have holding time under 10 years, yet the scrap rate is significantly lower in the first ten years. This implies that used EV subsidies will not divert many used EVs on their first transfer from being scrapped.

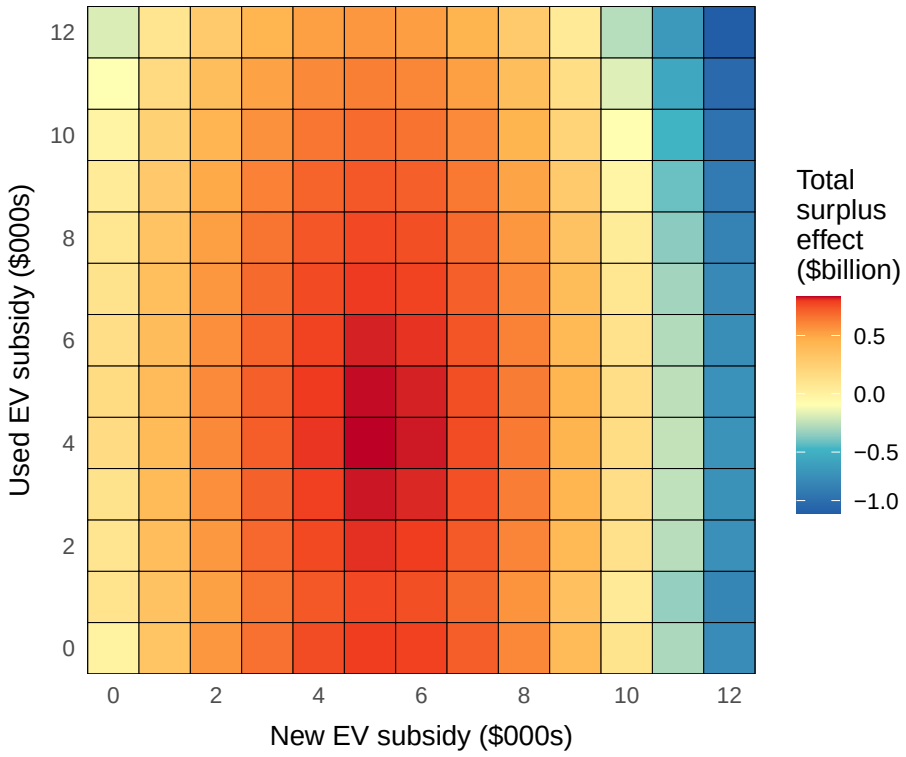
To target the vehicles at risk of scrappage more directly, we consider a policy where eligible EVs must be at less 10 years for used subsidies. Figure A21 presents a heatmap of total surplus effects in steady state given this criteria. Unlike Figure 5 in the body with age two eligibility, the optimal policy includes some used EV subsidies, and is in fact an even mixture of $5,000 new and used EV subsidies.

Figure A20: **New Vehicle Buyers' Holding Time and Scrap Rate**



Notes: This figure shows holding times for new vehicle buyers and vehicle scrap rates by age. The holding time, in maroon, is derived from the 2009 NHTS using the method described in Appendix E.2.2 after restricting to vehicles purchased new. The scrap rate, in grey, uses the fitted values for g_{ja} from equation (104) and averages by age using used sales.

Figure A21: **Total Surplus Effects of New and Used EV Subsidies**



Notes: Each square represents the total yearly surplus of the steady-state equilibrium relative to the no subsidy simulation.