Equitable Energy Transitions? The Efficiency and Distributional Effects of Subsidies for Used Electric Vehicles

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March 21, 2025

Abstract

We study the efficiency and distributional effects of the Inflation Reduction Act (IRA) tax credits for purchasing used electric vehicles (EVs), which aimed to address concerns that new EV tax credits primarily benefit higher-income buyers. We show theoretically that under certain conditions, tax credits for new versus used EVs have the *same* economic incidence because they interact through used EV resale values. However, using confidential dealership transaction data, we find that used EV prices increased by only a limited amount after the IRA was enacted and the tax credits became available, suggesting that the initial economic incidence fell primarily on EV buyers who were eligible for the credit. Bunching of transaction prices below the credit's $25,000 price threshold increased markedly in 2024, when buyers could immediately receive the credit amount as a cash rebate. We then assess the long-run welfare effects of EV tax credits using a novel non-stationary dynamic structural model of new and used vehicle markets.

Keywords: Electric vehicles, Inflation Reduction Act, economic incidence.

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1 Introduction

Researchers and policymakers have long traditions of concern for the distributional effects of corrective policies. Are gas taxes and carbon taxes regressive (e.g., Poterba 1991; Goulder et al. 2019)? Do emissions trading programs generate "hot spots" in disadvantaged areas (e.g., Fowlie, Holland, and Mansur 2012)? How much more do local air pollution or climate change harm the poor (e.g., Currie, Voorheis, and Walker 2023; Carleton et al. 2022)?

The Inflation Reduction Act (IRA) electric vehicle (EV) tax credits are a leading example of efforts to prioritize equity in environmental policy. Historically, new electric vehicles were expensive and largely bought by higher-income people, so EV subsidies were likely regressive. To reduce this regressivity, the IRA revised EV subsidies to include buyer income and vehicle price limits, and the law also introduced novel tax credits for transacting *used* electric vehicles. The rationale for these novel credits was that they might encourage the transition to EVs while also benefitting used car buyers, who are generally lower-income. However, the economic incidence of used vehicle transaction credits could be quite different from their statutory incidence. Moreover, equity could be in tension with environmental goals: a primary way that used EV transaction credits might increase the stock of EVs on the road is through increasing the expected resale price of new EVs, but this price increase would mechanically reduce any benefits to used EV buyers. Evaluating these tax credits is important, as the new and used vehicle credits are projected to cost taxpayers hundreds of billions of dollars (Bistline, Mehrotra, and Wolfram 2023) and there are regular proposals to repeal all or part of the IRA (Climate Power 2024).

This paper evaluates the efficiency and distributional effects of the IRA's used EV subsidies and compares these subsidies to new EV subsidies and other alternatives. We do this using unusually rich vehicle market microdata, quasi-experimental analyses using event study and bunching estimators, and a novel dynamic structural model of new and used vehicle markets designed to capture key features of the IRA policy design.

We begin with a stylized analytical model to fix ideas. In the model, firms sell a homogeneous durable good (e.g., an EV, with positive consumption externalities relative to its alternative) in symmetric imperfect competition. New EV buyers use the good for one period before selling to used vehicle buyers or scrappers, who use the vehicle for one period before it dies. The government can subsidize EVs when purchased new and/or when purchased used. The optimal policy is to subsidize ownership by the positive consumption externality plus the new EV markup. However, when all consumers are eligible to claim the tax credits and scrappage is fully inelastic, there is an equivalence result: new and used vehicle subsidies have the *same* effect in equilibrium, because new vehicle subsidies are passed through to used vehicle prices, and vice versa. However, this initial equivalence result breaks down under realistic conditions: when some consumers are ineligible, when scrappage is not fully inelastic, or when consumers are inattentive to resale

prices or the subsidy itself. This then motivates our empirical analyses, which compare the two subsidies under more empirically realistic conditions.

Our empirical work exploits an extraordinary collection of vehicle market microdata. We have transaction-level car dealership microdata from Cox Automotive, covering 44 and 39 percent of new and used vehicle transactions occurring at dealerships from 2022–2024. We add data on vehicle characteristics, the nation-wide stocks of vehicles registered, and the flows of vehicle transactions. To identify substitution patterns in our demand model, we add second choice data from the National Vehicle Experience Survey (NVES) plus microdata from the National Household Travel Survey (NHTS).

We use the price and registration data for two reduced-form analyses to estimate the effect of the subsidy on used EV prices. First, we estimate effects on prices of subsidy-eligible used EVs—that is, used EVs with prices under the IRA's $25,000 price limit for the buyer to receive the $4,000 tax credit—after the tax credit took effect in January 2023. This allows us to measure the short-run incidence of these credits. Using a triple-difference event study design, we estimate that prices of eligible relative to comparable ineligible EVs did not increase significantly relative to the relative trends for comparably priced GVs in the months after January 2023, and our 95 percent confidence intervals rule out effects of more than $1,272 for a vehicle that would have cost $20,000 in the absence of the tax credit. This implies that while the credits likely had some effect on used EV prices, we can easily rule out that used EV prices increased one-for-one with the tax credit. This implies that a good share of the benefits likely accrued to eligible used EV buyers.

Second, we estimate that used EV prices bunched at the $25,000 price limit starting in January 2023, which is consistent with some effect on used vehicle prices. We estimate that this bunching more than doubled in 2024, when the Treasury Department began to allow EV buyers to transfer tax credits to dealerships in exchange for immediate price reductions, instead of waiting for a credit when filing taxes. This implies that the dealership transfer significantly increased consumers' perceived value of the tax credits, perhaps due to earlier payment, increased certainty or salience, and/or the fact that dealership transfer made the credits refundable—i.e., that people without tax liability could claim them. We then use a novel bunching estimation strategy to find that the transaction price distribution below $25,000 shifted upwards by $250 due to the tax credit implementation in 2023 and next by $1,282 due to the dealership transfer change in 2024. Both of these results lie within the 95 percent confidence region for the price effects found in our event study analyses.

To better understand market dynamics and potential long-term effects, we present a structural model that captures the dynamics of non-stationary equilibrium in both the new and used durable goods market. The model incorporates automakers' pricing strategies for new products, consumers' product preferences, and car owners' scrapping decisions. Equilibrium outcomes include new product prices maximizing firms' profits, used goods prices ensuring market clearance in the used car market, scrap rates impacting the supply of used goods, and used EV credit premiums determining the price gap between EVs with and without

remaining used EV credits.

The simulation results from our model indicate significant and varied impacts of the used EV credits on the vehicle market. Upon the introduction of the policy, there is an immediate increase in the overall market value of vehicles, despite gradual increases in government expenditure. This rise is driven by consumers adjusting EV prices to reflect the anticipated future value of the credits. Initially, the positive demand shock from the policy predominantly impacts used EV prices rather than sales. The price increase is more pronounced for cheap EVs, which are more effective at leveraging the credits, making their credit premiums higher compared to expensive EVs. But, this demand shock is not just a short-term effect; it leads to a gradual increase in used EV sales as increased new EV sales gradually drive up used EV sales over the years. Moreover, higher EV prices reduce equilibrium EV scrap rates, further boosting the supply of used EVs in subsequent periods.

The policy also has a substantial impact on market dynamics between different types of vehicles. It shifts consumer demand from used gas vehicles (GVs) to used EVs, leading to a decrease in both the equilibrium price and sales of GVs. For example, the selling price of used EVs rises significantly—by approximately 9 percent initially and over 14 percent in later periods. Consequently, EVs with available credits experience lower scrap rates due to the used EV credit premium. Conversely, equilibrium scrap rates for old GVs increase due to their decreased prices. Similarly, scrap rates for EVs without remaining credits also rise under the policy as their prices decrease net of premiums.

The benefits of the policy are not uniformly distributed across all income brackets. High-income consumers, despite being ineligible for the used EV credits, indirectly benefit through higher resale values of their vehicles. On the other hand, low-income consumers experience direct benefits as the used EV credits exclusively target them. In addition, these direct benefits increase as government spending on credits grows over time. These findings underscore the complex but overall positive effects of the IRA's used EV credit policy on the automotive market. Our analysis aims to provide a comprehensive understanding of the IRA's efficiency and distributional impacts, offering valuable insights for policymakers involved in the transition towards vehicle electrification.

Our work relates to several literatures. We follow Berry, Levinsohn, and Pakes (1995) and Berry, Levinsohn, and Pakes (2004) to develop a structural model of demand and supply of new vehicles. Our model of the used vehicle market connects to the literature on dynamic models of durable goods, including Hendel and Nevo (2006) on consumer products such as laundry detergent; Gavazza (2011) on aircrafts; Gowrisankaran and Rysman (2012) on consumer electronics; and Hendel and Lizzeri (1999), Stolyarov (2002), Gavazza, Lizzeri, and Roketskiy (2014), and Gillingham et al. (2023) on vehicles. We build more directly on static models of the used vehicle market Bento et al. (2009) and Jacobsen and Benthem (2015), and Jacobsen et al. (2021) in order to capture non-stationarity in the market for electric vehicles.

We contribute to a broad literature evaluating environmental regulations in the automobile industry, such

as the Corporate Average Fuel Economy (CAFE) standards Goldberg (1998), Austin and Dinan (2005), Knittel (2011), Jacobsen (2013), and Wang and Miao (2021), other emissions standards Anderson et al. (2011); Klier and Linn (2016); Ito and Sallee (2018); Jacobsen et al. (2023); Lin and Linn (2023), and zero-emissions vehicle mandates Armitage and Pinter (2022) and Kwon (2023). Jacobsen et al. (2023) find that policies such as the exhaust standards from the U.S. Clean Air Act are not cost-efficient because they do not regulate older vehicles, which are the source of the majority of emissions from the U.S. automobile industry. We are most closely related to literature on tax credits for hybrids and electric vehicles Gallagher and Muehlegger (2011); Borenstein and Davis (2016); Sheldon and Dua (2019); Linn (2022); Muehlegger and Rapson (2022); Cole et al. (2023); Slowik et al. (2023), and we contribute to this literature by evaluating tax credits in the used vehicle market.

Finally, we connect to papers assessing the pass-through of credits in the automobile market. Busse, Silva-Risso, and Zettelmeyer (2006) measure the pass-through of cash incentives from automobile manufacturers to dealerships and customers, which are both relevant agents in our setting of the used vehicle market. Sallee (2011) and Gulati, McAusland, and Sallee (2017) measure the incidence of tax credits for hybrid vehicles, and Barwick et al. (2023) measure the incidence of tax credits for electric vehicles. In addition to the focus on used electric vehicles, our policy setting differs through the cap on sale price for qualifying vehicles.

Sections 2–10, respectively, present the policy background, stylized analytical model, data, reduced-form estimation, structural model, estimation, counterfactual simulation procedure, simulation results, and conclusion.

2 Policy Background

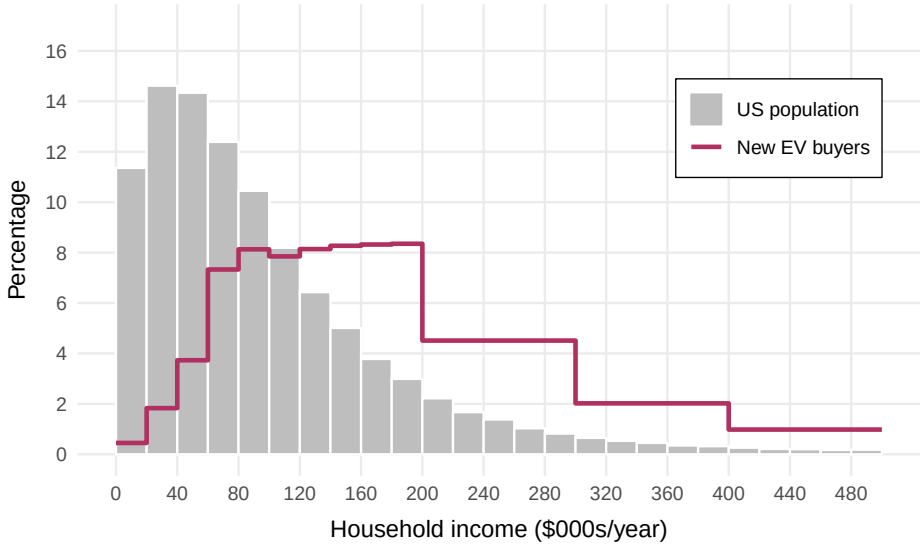
The Used Clean Vehicle Credit from the Inflation Reduction Act (IRA) is a tax credit for the purchase of a pre-owned electric or plug-in hybrid vehicle equaling 30 percent of the sale price up to a maximum level of $4,000. The tax credit is non-refundable, but taxpayers do not need to itemize deductions to claim it.

There are eligibility requirements based on buyer, transaction, and vehicle characteristics. Buyers must be individuals (not corporations) with incomes below $150,000 for married couples filing jointly, $112,500 for heads of households, and $75,000 for all others. The purchase must be made from a licensed dealer at a purchase price of $25,000 or less. The purchase must be made for the purpose of using the vehicle rather than resale, and this use must be primarily in the U.S. The vehicle must be a light-duty vehicle (less than 14,000 pounds), must be at least two years old, and must have battery capacity of at least 7 kilowatt hours. The vehicle cannot have already been transferred after August 16, 2022 to a qualified buyer. The IRS records the VINs of eligible transactions, so consumers cannot game the credit by repeatedly transacting the same vehicle.

The Used Clean Vehicle Credit could be claimed on transactions starting on January 1, 2023. During 2023, buyers received the credit by claiming it on personal income taxes. Since January 1, 2024, this credit may also be applied at the point of sale. This means that a buyer can transfer the credit to the dealer and apply the credit towards the purchase of the vehicle. The dealer must register with the IRS to receive an advance payment of the value of the credit.

Income limits on EV subsidies may be particularly restrictive given that EV buyers are relatively high-income. Figure 1 shows household income of the US population against the income of new EV buyers from the NVES second choice data. The US population income distribution has a substantially higher percentage of mass below $100k.

Figure 1: **Histogram of New EV Buyers and US Population Income**



Notes: Income is truncated at $500k. The US population income distribution is household income drawn from the 2023 American Community Survey (ACS). New EV buyers income is from the Second Choice data, with binned values roughly every $20k up until $200k then spaced every $100k.

The impacts of income limits and used subsidies in general are of interest to more entities than the US federal government and even more broadly than the US itself. In Table 1 we present a global list of locations with new and used EV subsidies active in 2024, noting whether they included income and price limits. We include only observations that offer purchase subsidies (e.g., direct rebates or tax credits) rather than other incentives such as VAT waivers, import tax waivers, or income tax deductions. Table 1 demonstrates that not only are new EV subsidies widely adopted, but used EV subsidies are as well. In general, used EV subsidies are more likely to be offered by sub-national governments, such as US states or Canadian provinces.

Table 1 also shows that price limits for eligible transactions are nearly ubiquitous while income limits

Table 1: **List of New and Used EV Subsidies Active 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	$3,500	$1,750		✓
Austria	$5,450			✓	Newfoundland and Labrador	$1,750	$1,750		
Croatia	$9,810			✓	Nova Scotia	$2,100	$1,400		✓
Cyprus	$9,810	$9,810		✓	Northwest Territories	$3,500			✓
France	$4,360		✓	✓	Prince Edward Island	$3,500	$3,500		✓
Flanders, Belgium	$4,360	$3,270		✓	Quebec	$2,800	$1,400		✓
Greece	$8,720				Yukon	$3,500			
Iceland	$6,750	$5,250		✓	**Australia**				
Ireland	$3,815			✓	Queensland	$3,840		✓	✓
Italy	$4,905		✓		Western Australia	$2,240			✓
Lithuania	$5,450	$2,725		✓	**United States**				
Luxembourg	$8,720				United States (federal)	$7,500	$4,000	✓	✓
Malta	$11,990				California	$7,500	$7,500	✓	✓
Netherlands	$3,216	$2,180		✓	Colorado	$6,000			✓
Poland	$10,400		✓	✓	Connecticut	$4,500	$5,000	✓	✓
Portugal	$4,360			✓	Delaware	$2,500	$2,500		✓
Romania	$6,813				Illinois	$4,000	$4,000		
Slovenia	$7,848	$3,270		✓	Maine	$7,500	$2,500	✓	✓
Spain	$9,810			✓	Maryland	$3,000			✓
Asia					Massachusetts	$5,000	$5,000	✓	✓
Singapore	$18,750	$18,750			Minnesota	$2,500	$600		✓
Japan	$5,695			✓	New Jersey	$4,000		✓	✓
Thailand	$2,900			✓	New York	$2,000			✓
China	$2,800				Oregon	$7,500	$5,000	✓	
South Korea	$4,485		✓	✓	Pennsylvania	$4,000	$4,000	✓	✓
Canada					Rhode Island	$3,000	$2,500	✓	✓
Canada (federal)	$3,500			✓	Vermont	$5,000	$5,000	✓	✓
British Columbia	$2,800		✓	✓	Washington	$5,000	$2,500	✓	✓
Manitoba	$2,800	$1,750		✓	State utilities	various	various	✓	✓

Notes: This list includes subsidies that were active at any point in 2024. Subsidy amounts are the maximum offered. We only include locations that offer purchase subsidies (through either direct rebates or tax credits) rather than other incentives such as VAT waivers, import tax waivers, or income tax deductions. Sources include official government websites and European Alternative Fuels Observatory data such as European Commission 2024.

are less common. From an eligibility perspective, income and price limits can serve the same purpose, assuming that more affluent citizens purchase higher priced vehicles, so the higher adoption of price limits is noteworthy. Our analysis of the effectiveness of used subsidies in conjuction with their relationship to income and price limits are informative to policymakers who need to limit expenditures while encouraging EV adoption. This need is demonstrated by a number of the subsidies in Table 1 which were suspended at some point in 2024 due to the exhaustion of appropriated funds in the current fiscal year.

3 Stylized Analytical Model

3.1 Setup

To clarify the effects and incidence of subsidizing new versus used vehicle transactions, we begin with a stylized analytical model. The model considers the life cycle of a durable good (EVs) with less negative consumption externalities than its alternative (GVs). The government can subsidize purchases of the good when new and/or when used. We derive the incidence of these subsides in addition to their quantity effects and the optimal policy.

In the model, EVs live for two periods. In their first period, new EVs are produced and sold at price p_{nt} and driven by new vehicle buyers. In their second period, the now-used EVs are either resold to dealerships at price $p_{u,t+1}$ or are scrapped at a constant price v_s. Let $\tilde{p}_{u,t+1}$ denote the expectation of $p_{u,t+1}$ for vehicle buyers at time t. After their second period, all remaining used vehicles are scrapped at zero price.

Vehicles sold to the dealership must be in dealership-used condition. Suppose that new vehicle buyers after period one receive a quality draw ζ_i from an absolutely continuous distribution P defined on [0,1]. Let ψ be a reconditioning cost parameter so that $\zeta_i\psi$ is the cost of owner i to bring their vehicle to dealership-used condition. Then vehicle i will be reconditioned if and only if $p_{u,t+1} - \zeta_i\psi \geq v_s$. The condition to scrap is the compliment of the condition to recondition, therefore, define the (market) scrap rate $g(p_{u,t+1}) \coloneqq 1 - P((p_{u,t+1} - v_s)/\psi)$.[1] The resale value $\tilde{v}_i$ and its expectation $\tilde{V}$ from the perspective of time t are then

$$\tilde{v}_i(\zeta_i) = v_s \cdot \mathbb{1}\left\{\zeta_i \geq \frac{\tilde{p}_{u,t+1} - v_s}{\psi}\right\} + (\tilde{p}_{u,t+1} - \zeta_i\psi) \cdot \mathbb{1}\left\{\zeta_i \leq \frac{\tilde{p}_{u,t+1} - v_s}{\psi}\right\} \tag{1}$$

$$\tilde{V} \coloneqq \mathbb{E}_P\left[\tilde{v}_i(\zeta_i)\right] = v_s + \left(1 - g\left(\frac{\tilde{p}_u - v_s}{\psi}\right)\right) \cdot (\tilde{p}_u - v_s) - \psi \int_0^{\frac{\tilde{p}_u - v_s}{\psi}} x dP(x) \tag{2}$$

We note this setup has the nice result that $\frac{d\tilde{V}}{d\tau_x} = (1-g)\frac{d\tilde{p}_u}{d\tau_x}$ for $x \in \{n, u\}$.

Define ϕ as the negative externality reduction (or equivalently, positive externality) from consuming EVs relative to the alternative (GVs). The government offers new and used vehicle purchase subsidies $\{\tau_n, \tau_u\}$,

[1] We assume throughout that $p_{u,t+1}$, ψ, and v_s are such that $0 \leq g(p_{u,t+1}) \leq 1$

which are paid to buyers. Share μ of buyers are eligible to receive the subsidies, while share $1-\mu$ are ineligible, e.g. due to the IRA income restrictions. Scrapped vehicles are not eligible and we assume they generate no externality.[2]

We allow consumers to substitute across the new and used vehicle markets, but to simplify the demand functions, we make several assumptions. First, we assume that consumers' utility is quasilinear in the numeraire, so there are no income effects. Second, to allow for aggregation across eligibility types, we assume that aggregate EV demand is (locally) linear and that eligible and ineligible buyer types have the same demand function.[3] Third, we assume that own price derivatives are greater in absolute value than cross price derivatives, which implies that own demand elasticities are greater than cross elasticities.

Under these assumptions, new vehicle demand is $D_n := D_n(p_{nt} - \mu\tau_n - \tilde{V}, p_{ut} - \mu\tau_u)$, and used vehicle demand is $D_u := D_u(p_{nt} - \mu\tau_u - \tilde{V}, p_{ut} - \mu\tau_u)$. Let D_n^1 denote the derivative of D_n with respect to its first argument, and analogously for D_n^2, D_u^1, and D_u^2. Then by our assumptions, $|D_n^1| > |D_n^2|$ and $|D_u^2| > |D_u^1|$ with $D_n^1, D_u^2 \leq 0$ and $D_n^2, D_u^1 \geq 0$.

We assume new EVs are produced at constant marginal cost c with aggregated supply denoted $S := S(p_n)$ and $S' > 0$.

Equilibrium is a set of prices $\{p_{nt}, p_{ut}\}$ such that (i) consumers and firms optimize, (ii) new good buyers correctly forecast the resale price: $\tilde{p}_{u,t-1} = p_{ut}$, and (iii) markets clear: $S = D_n$ and $D_u = (1-g) \cdot S$. The steady state of our model is when $p_t = p_{t+1}$ for both new and used prices. We drop the subscript t below when considering steady-state contexts.

Define W as total surplus over the life cycle of one generation of EVs. We assume that the government can use lump-sum taxes and transfers, so the marginal cost of public funds equals one. In addition, we assume that the dealership-used market and scrap markets are in perfect competition and generate zero profits. Therefore, W is the sum of consumer surplus (summing both eligible and ineligible types), producer surplus, and positive externalities net of government spending:

[2] Some used vehicles are exported to Mexico and other countries and thus continue generating externalities, but Olguín, Iskakov, and Kendall (2023) report that only 5 to 13 percent of vehicles deregistered in the US are exported.

[3] The linearity assumption is with no loss of generality in the case with full eligibility.

$$
\begin{aligned}
&W(\tau_n, \tau_u, \mu) = \\
&\underbrace{\mu \cdot \int_{p_n-\tau_n-V}^{\infty} D_n(x,y)dx + (1-\mu)\cdot \int_{p_n-V}^{\infty} D_n(x,y)dx + D_n(p_n-\mu\tau_n-V, p_u-\mu\tau_u)\cdot(p_n-c+\phi)}_{\text{New EV CS, PS, and externality}} \\
&\quad \underbrace{-\mu\tau_n D_n(p_n-\tau_n-V, p_u-\tau_u)}_{\text{New EV subsidy}} + \underbrace{\mu \cdot \int_{p_u-\tau_u}^{\infty} D_u(x,y)dy + (1-\mu)\cdot \int_{p_u}^{\infty} D_u(x,y)dy}_{\text{Used EV CS}} \\
&\quad + \underbrace{D_u(p_n-\mu\tau_n-V, p_u-\mu\tau_u)\cdot(\phi)}_{\text{Used EV externality}} \underbrace{-\mu\tau_u \cdot D_u(p_n-\tau_n-V, p_u-\tau_u)}_{\text{Used EV subsidy}} \qquad (3)
\end{aligned}
$$

3.2 Optimal Policy

In steady state equilibrium, the optimal policy will involve full eligibility and a mix of both new and used subsidies.

Proposition 1 (Optimal subsidies): In steady state, the total surplus-maximizing subsidies are

$$
\begin{aligned}
\mu^* &= 1, \\
\tau_n^* &= p_n - c + \phi, \\
\tau_u^* &= \phi
\end{aligned} \qquad (4)
$$

Proof: see Appendix A.1.

The optimal policy is exactly that of the Pigouvian optimal subsidy: subsidize each market by the externality plus any markup. The key takeaway from Proposition 1 is that new and used subsidies are not interchangeable in a general setting where scrappage is elastic. Therefore, from the perspective of a social planner trying to maximize welfare, it is necessary to use both new and used subsidies. However, if we take a step back and suppose scrappage is perfectly inelastic, then new and used subsidies start to resemble taxing different sides of the same market, which of course are equivalent. We now formalize this result.

Proposition 2 (Symmetry): If and only if scrappage is fully inelastic ($g' = 0$), there exists $x, y \in \mathbb{R}^{>0}$ such that the policies $\{\tau_n, \tau_u\}$ and $\{\tau_n + x, \tau_u - y\}$ generate the same steady-state equilibrium quantities. If they exist, $x = y \cdot (1-g)$.

Proof: see Appendix A.2.

The intuition for this lemma is as follows. By having used prices enter the effective price of new vehicles, the new and used markets are directly linked. Therefore, this is just a nonstandard application of the principle that statutory incidence is independent of economic incidence.

Note that this lemma implies that if $g' = 0$ then a combined tax change $(1-g)\Delta\tau_n$ and $-\Delta\tau_u$ will have no effect on equilibrium market outcomes. Therefore, an application of this corollary is that if scrappage

is perfectly inelastic, there will exist a continuum of optimal policies. In particular, in the steady state an optimal policy for a social planner is subsidizing only new vehicles and setting $\tau_u^* = 0$.

This result highlighting the importance of scrap elasticity nicely primes our following discussion on incidence and quantity effects, during which scrap elasticity plays a key role in illuminating how new and used subsidies interact with the market.

3.3 Incidence and Quantity Effects

We now consider incidence: the effect of marginal subsidy changes on equilibrium prices. First, we consider a restricted steady state setting followed by the general setting. After we consider the short-run effects of a surprise used EV subsidy. Throughout we also highlight how new and used subsidy affect the total quantity of new and used EVs demanded.

3.3.1 Restricted Steady State Effects

We start by analyzing the effects in the steady state, which allows equilibrium used EV supply to adjust. As a primer, we first analyze a simplified version assuming no substitution between the new and used markets, along with perfectly inelastic scrappage.

Proposition 3 (Restricted steady state effects): If scrappage is perfectly inelastic ($g' = 0$) and there is no substitution ($D_n^2 = D_u^1 = 0$), then the effects of marginal subsidy changes on steady-state equilibrium prices are

$$\frac{dp_n}{d\tau_n} = \underbrace{\frac{\mu D_n^1 D_u^2}{D_n^1 D_u^2 - S'(1-g)^2 D_n^1 - S' D_u^2}}_{:=\Lambda^R} \geq 0, \quad \frac{dp_n}{d\tau_u} = (1-g)\frac{dp_n}{d\tau_n} \tag{5}$$

$$\frac{dp_u}{d\tau_n} = \frac{\mu D_n^1 S'(1-g)}{\Lambda^R} \leq 0, \quad \frac{dp_u}{d\tau_u} = \frac{\mu \left[D_n^1 D_u^2 - D_u^2 S'\right]}{\Lambda^R} \geq 0. \tag{6}$$

The symmetric quantity effects are

$$\frac{dD_u}{d\tau_n} = (1-g)\frac{dD_n}{d\tau_n} = (1-g)S'\frac{dp_n}{d\tau_n} \geq 0 \tag{7}$$

$$\frac{dD_u}{d\tau_u} = (1-g)\frac{dD_n}{d\tau_u} = (1-g)^2 S'\frac{dp_n}{d\tau_n} \geq 0 \tag{8}$$

Proof: see Appendix A.3.

In this restricted setting, Proposition 3 shows us that used subsidies increase both new and used prices, but the used prices increase more. On the other hand, new subsidies raise new prices, which will lead to a greater supply of used vehicles in the steady state (since g is fixed), which depresses used prices. Note that all incidence rates are scaled by eligibility μ and in effect are weakly less than 1 in absolute value.[4]

[4]Strictly speaking $\frac{dp_u}{d\tau_n}$ need not be bounded by 1, but $\frac{dV}{d\tau_n}$ is, so more precisely the change in effective prices are all bounded by 1.

Therefore, tighter eligibility constraints (decreased μ) implies smaller price effects and thus a more acute benefit accrues to the eligible recipient.

Taken together, Proposition 3 demonstrates that both new and used EV subsidies (i) benefit eligible buyers, (ii) harm ineligible buyers, and (iii) benefit buyers in the other (new or used) market. The quantity effects illustrate our symmetry result above, with the extra addition that used quantities rise by $(1-g)$ times the change in new quantities.

3.3.2 General Steady-State Incidence

We turn now to incidence in the full steady-state model, followed by quantity effects in the next section.

Proposition 4 (Steady-state effects): the effects of marginal subsidy changes on steady-state equilibrium prices are

$$\begin{aligned}
\frac{dp_n}{d\tau_n} &= \frac{\mu\left[D_n^1 D_u^2 - D_u^1 D_n^2) + D_n^1 g' S\right]}{\Lambda} \geq 0, \quad \frac{dp_n}{d\tau_u} = \frac{\mu\left[(1-g)(D_n^1 D_u^2 - D_n^2 D_u^1) + g' S D_n^2\right]}{\Lambda} \lessgtr 0 \\
\frac{dp_u}{d\tau_n} &= \frac{\mu\left[D_n^1 S'(1-g) - D_u^1 S'\right]}{\Lambda} \leq 0, \quad \frac{dp_u}{d\tau_u} = \frac{\mu\left[(D_n^1 D_u^2 - D_n^2 D_u^1) - D_u^2 S' + D_n^2 (1-g) S'\right]}{\Lambda} \geq 0.
\end{aligned} \tag{9}$$

where $\Lambda = \Lambda^R + D_n^2\left[S'(1-g) - D_u^1\right] + D_u^1 S'(1-g) + S g'\left[D_n^1 - S'\right] \geq 0$.

Proof: see Appendix A.4.

Starting with the comparative statics of used subsidies, we see that p_u rises unambiguously due to the direct effect of the policy and increased substitution to used vehicles. Meanwhile, there is ambiguity in the directional change of p_n. The positive force originates from the rise in p_u which increases the resale value of new vehicles (the first term), while the negative force is the decrease in the scrap rate which encourages substitution to the used market (the second term). For p_n to decrease we would require both elastic scrappage and high substitution by consumers ($D_n^2 >> 0$). Compared to the restricted case, the denominator is increased due to greater stock accumulation from more flexible substitution patterns.

Turning to the effects of new subsidies, we see the expected results. Namely, new subsidies will enter new vehicle demand raising p_n, which will eventually increase the supply of used vehicles thus depressing p_u. Changes in scrappage do not create ambiguity here because the new subsidies do not directly affect the decision whether to scrap a vehicle. Rather, scrappage will change in response to the increased new vehicle stock, which will not overwhelm the expected directional changes (i.e., scrappage will not increase by more than dS).

Under most cases we will have all four incidence results strictly bounded between (-1,1) in effect size, meaning the subsidies change market prices less than one-for-one.[5] Thus, both new and used EV subsidies

[5]For $\frac{dp_u}{d\tau_x}$ we only need $(1-g)\frac{dp_u}{d\tau_x}$ bounded. The absent lower bound on $\frac{dp_n}{d\tau_u}$ does not matter below.

(i) benefit eligible buyers, (ii) harm ineligible buyers, and (iii) benefit buyers in the other (new or used) market.

The eligibility share μ multiplies the numerator in each equation in Proposition 4. As μ decreases, the effects on demand also decrease, which in turn mutes price effects. This magnifies the effects on eligible buyers, because they claim the full subsidy with smaller offsetting vehicle price increases. Correspondingly, this decreases the effects on ineligible buyers and buyers in the other (new or used) market.

Two types of inattention could affect these results. First, if buyers are unaware of the subsidy, uncertain as to whether they will be able to claim it, or discount it for some other reason, this would enter the model like a decrease in the eligibility share μ, muting all price effects. Second, if new EV buyers are unaware of or inattentive to the potential effects of the used EV credit on resale prices, this would enter the model like a discount factor ρ on the resale price p_u, muting the effects of the used EV credit on new vehicle prices.

3.3.3 General Steady-State Quantity Effects

We now turn from analyzing price effects to quantity effects of new and used EV tax credits in general steady-state equilibrium. This analysis helps articulate how new and used subsidies interact in the market and the ways in which they are different.

Proposition 5 (Quantity Effects): $\frac{dD_n}{d\tau_n}, \frac{dD_u}{d\tau_u} \geq 0$ while $\frac{dD_n}{d\tau_u}, \frac{dD_u}{d\tau_n}$ are ambiguous in sign.

Proof: see Appendix A.5.

There are two implications of this result. First, we see that own good quantities are always raised by subsidies in the long-run. This is somewhat non-trivial because the price effects in Proposition 4 can point in different directions for a change in new EV credits and the net effect on effective prices is unclear. This corollary demonstrates that the pass-through into higher prices cannot overwhelm the decrease in own good net prices felt from increasing new or used tax credits.

The more interesting result is that new and used tax credits have very different effects on the number of vehicles scrapped. Scrappage depends on the seller's effective price in the used vehicle market. Under new tax credits this equals the buyer's price of p_u, which decreases by Proposition 4, therefore, it is clear why scrappage increases. Under used tax credits the seller's price is p_u while the buyer's price is $p_u - \tau_u$. This wedge allows the seller's price to increase (per Proposition 4) driving down scrappage (recall used subsidies are not available for scrapped vehicles).

The following proposition considers whether own good subsidies, relative to cross good subsidies, are better at raising own good quantities

Proposition 6 (Relative Quantity Effects):

$$\frac{dD_n}{d\tau_n} - \frac{dD_n}{d\tau_u} \geq 0 \tag{10}$$

$$\frac{dD_u}{d\tau_n} - \frac{dD_u}{d\tau_u} \lesseqgtr 0 \tag{11}$$

Proof: see Appendix A.6.

From Corollary 1 we know that $\frac{dD_n}{d\tau_n}, \frac{dD_u}{d\tau_u} > 0$. Therefore, this corollary tells us that the increase in new demand from changing τ_n is larger than changing τ_u. The ambiguity in the case of used demand relates to how used subsidies are important if scrappage is elastic, but they also only enter a rate of (1-g), making them less effective per dollar if $g' = 0$. A sufficient condition for equation 11 to be negative (i.e., used subsidy are superior at raising D_u) is for $|g'S| \geq |S'(1-g)|$, meaning scrappage is sufficiently elastic. To connect back to the symmetry result, the equations in Proposition 6 are identically zero exactly when $g' = 0$.

3.3.4 Short-Run Incidence of Surprise EV Subsidy

In the months and years after the IRA was passed, its used EV tax credits affect demand for used EVs, whose supply cannot adjust because earlier model years (MYs) are no longer in production. We can analyze this short-run incidence in our model by considering the effect of a marginal increase in τ_u after the supply of used vehicles has been fixed at S_{t-1}, although we still allow the scrap rate to change which is a key aspect of the short-run dynamics. Therefore, our short-run market clearing conditions are

$$D_n(p_{nt} - \mu\tau_n - \tilde{V}, p_{ut} - \mu\tau_u) = S(p_{nt}) \tag{12}$$

$$D_u(p_{nt} - \mu\tau_n - \tilde{V}, p_{ut} - \mu\tau_u) = (1 - g(p_{ut}))S_{t-1}. \tag{13}$$

In our results below, we will consider $\frac{d\tilde{p}_{u,t+1}}{d\tau_u}$ as exogenous to the model, since the system need not equilibrate in one period.

Proposition 7 (Short-Run Incidence): the effects of marginal subsidy changes on short-run prices are

$$\frac{dp_{ut}}{d\tau_u} = \frac{\mu\left[(D_n^1 D_u^2 - D_u^1 D_n^2) - D_u^2 S'\right] - S' D_u^1 (1 - g(p_u))\frac{d\tilde{p}_{u,t+1}}{d\tau_u}}{\Lambda_{SR}} \lesseqgtr 0 \tag{14}$$

$$\frac{dp_{nt}}{d\tau_u} = \frac{\mu S_{t-1} g' D_n^2 + \frac{d\tilde{p}_{u,t+1}}{d\tau_u}\left[S_{t-1} g' D_n^1 + (1 - g(p_u))(D_n^1 D_u^2 - D_u^1 D_n^2)\right]}{\Lambda_{SR}} \lesseqgtr 0. \tag{15}$$

where $\Lambda_{SR} = (D_n^1 D_u^2 - D_n^2 D_u^1) - S' g' S_{t-1} - S' D_u^2 + D_n^1 S_{t-1} g' > 0$.

Proof: see Appendix A.7.

The ambiguous nature of the short-run effect of used subsidies hinges on the magnitude of the change in used prices expectations. A sufficiently large change in expectations would lower the effective price of new vehicles, thus raising p_n directly and lowering p_u through substitution to the new market. On the other hand,

if we consider the lower extreme that consumers are completely inattentive to the policy (i.e., $\frac{d\tilde{p_{u,t+1}}}{d\tau_u} = 0$), then the importance of substitution to the new market falls. Consequently, the direct effect of the used subsidy on used prices becomes primal, which induces higher used prices and lower new prices (through substitution).

If we consider the intermediate case where expectations rise by a moderate amount, we can see two forces at play affecting both new and used prices. First, the moderate increase pushes the new price upwards reflecting the added value to owning a new vehicle (the second term in dp_{nt}). Second, the scrap rate has the potential to decrease if p_u rises, this leads to more supply in the used EV market decreasing demand for new vehicles and depressing p_n (this is the first term in (dp_{nt}). A sharp fall in scrappage could be sufficient to create an overall negative effect on new prices. In reality S_{t-1} could be very large due to many model years of used EVs, which would strengthen the effect of scrap elasticity. The two forces affecting used prices are the direct positive effect of the policy and the negative effect of substitution to the new market. In the case where there is no new-used substitution ($D_n^2 = D_u^1 = 0$), perfectly inelastic scrappage ($g' = 0$), and consumers are fully inattentive ($\frac{d\tilde{p_{ut+1}}}{d\tau_u} = 0$), p_{ut} rises by μ, implying full incidence on the sellers if $\mu = 1$.

Now consider for a moment late-model used vehicles, which are rarely scrapped and will have low scrappage elasticity, then both new and used prices will likely rise under moderate expectations about future price increases. Furthermore, inspection of the incidence results under sufficiently low scrappage elasticity and moderate expectations shows that they are also bounded above by 1. Under these assumptions, consider the implications for different consumer groups if $\mu < 1$. Eligible used vehicle buyers benefit from lower subsidy-inclusive prices, while ineligible used vehicle buyers are harmed by higher subsidy-exclusive prices. People who owned EVs at the time of the policy announcement, who in reality would be mostly wealthier people who had previously bought new EVs, receive a windfall when the resale price increases.

While simple and stylized, this analytical model clearly sets up our empirical agenda. In Section 5, we use reduced-form approaches to estimate the short-run incidence of the used EV tax credits. In Section 8, we simulate the long-run effects of those credits using a structural model that accounts for the share of consumers that are eligible for the tax credits, the scrappage elasticity, the possibility of multiple used transactions for the same vehicle, and other realistic forces.

4 Data

We use transaction-level microdata covering July 2021 to December 2024 from Cox Automotive, including both new and used transactions. These data cover about 44 and 39 percent of new and used dealership transactions, respectively.[6] We observe the week of the transaction, VIN, lease terms, transaction price

[6]Measured from 2022 through Q1 2024 based on comparison with Experian data

(excluding taxes, fees, and aftermarket charges), rebate amounts, dealership identifier, state, and buyer zip code.

We also use registration data from Experian, covering the entire US market from January 2022 through March 2024. We observe monthly sales of new and used vehicles grouped by make, model year (MY), vehicle model, powertrain, trim, buyer type (individual, organization, or government), and seller type (dealership or individual). In addition, we observe the total stock of registered vehicles at the end of Q3 2022 and 2023. Summary statistics on the transaction data are in Panel B of Table 2.

Our sample for reduced-form estimation and structural modeling has several restrictions. First, we exclude leased vehicles. Second, we remove vehicle makes that have an average selling price over $200,000. Third, we trim extreme values by removing the upper and lower 0.5 percent for price, and the upper 0.5 percent for mileage.

We impose further restrictions for the sample used in the reduced-form analysis. Specifically, we include only used vehicles with MY between 2011 and 2022, inclusive. We restrict to these MY cutoffs since the first EVs in the data are of MY 2011, and we exclude older GVs to construct the relevant control group. We also exclude model-by-MY combinations with average transaction prices above $50,000, which tend to be luxury models or sports cars. The vast majority of transactions within these model-by-MY combinations are well above the tax credit's $25,000 transaction price cutoff, and any transactions closer to that price may represent unusual situations or damaged vehicles. In Panel A of Table 2 we show summary statistics of our event study cleaned Cox dataset.

For the structural model, we explicitly exclude sports cars due to their overall small transaction share and the differences in market trends compared to the overall car market. In addition, we classify vehicles by fuel type as either electric, gas, plug-in hybrid, or hybrid. For each make, MY, and fuel type, we aggregate transactions to the body style level, with observations in {Car, SUV, Truck}.[7] We find that aggregating to the body style, make, fuel type level sufficiently separates externality profiles and price levels, which are related to important outcomes of the subsidies.

We impose a single body style for each model across all MYs to more accurately represent changes in vehicle stocks over time. Grouping observations at the body style level, as opposed to the model level, is useful because manufacturers change vehicle models relatively frequently, creating sharp discontinuities in vehicle stocks at the level of make, model, and MY. We also account for this directly by grouping renamed models under a common model name. In an effort to reduce the choice set cardinality, as a final step we group makes that are defunct or have fewer than one million vehicles in Q3 2023 into a larger make under the same manufacturer, or absent that, into an "Other" category. We are left with 28 distinct makes.

Finally, we use second choice data from the National Vehicle Experience Survey (NVES), which surveys

[7] In the data we also observe vans, but to limit choice set size we group fullsize-vans into Trucks and minivans into SUVs.

Table 2: **Summary Statistics**

	(1) Mean	(2) Std. dev.	(3) Min	(4) Max	(5) Obs.
Panel A: Cox Data					
Model year	2018	3	2011	2022	11,928,372
EV	0.02	0.13	0	1	11,928,372
Price ($000s)	26.69	10.7	0.001	196.415	11,928,372
APR (%)	10.59	5.88	0.01	35	6,360,071
Mileage (000s)	54.23	34.62	0.501	258.168	11,458,335
Panel B: Experian Data					
Model year	2016.17	6.08	2002	2023	3,916,952
EV	0.03	0.15	0	1	3,916,952
Used	0.71	0.34	0	1	3,916,952
Monthly transactions	3,947,861	305,594	3,387,350	4,370,030	12
Panel C: Second Choice Data					
EV first choice	0.09	0.30	0	1	273,290
EV second choice	0.03	0.20	0	1	273,290
Considered other choice	0.42	0.50	0	1	273,290
Income ($000s)	147.66	150.52	10	875	214,237

Notes: EV includes both pure EVs and PHEVs. Panel A provides summary statistics of the event study cleaned Cox data. Panel B provides statistics for our Experian sales data. Panel C contains statistics of survey data from the NVES of new vehicle buyers.

new car buyers. These data are use in the estimation of structural model parameters. We observe the income of buyers, the make, model, and (sometimes) trim of the vehicle they purchased, and whether they considered a different vehicle along with that vehicle's information. We match vehicles to their fuel types, albeit imperfectly. In Panel C of Table 2 we display summary statistics of the second choice data.

5 Reduced-Form Evidence: Effects on Vehicle Prices

This section aims to assess the effects of the Used Clean Vehicle Credit on vehicle prices. We implement two strategies to measure price effects: a triple-difference event study comparing cheap and expensive EVs and GVs and a novel bunching analysis using the excess mass in the price distribution located at the $25k

price limit to find the implied shift in the price distribution. We use these strategies to find the price effect of the tax credit implementation on January 1, 2023 and the start of dealership credit transfers on January 1, 2024.

The price effect of the tax credit implementation on January 1, 2023 is informative of the pass-through of the credit and therefore the distributional consequences of the policy. The statutory incidence of the credit directs benefits towards lower-income used vehicle buyers, but the distributional consequences of this policy depend on the economic incidence of the credit. If used vehicle prices respond, some of this benefit may be captured by the car dealerships and vehicle resellers, who are likely to have higher incomes.

On January 1, 2024, consumers could claim the credit at the point of sale from the dealer rather than needing to file the claim with their taxes (IRS 2024b). Consumers may prefer the dealership transfer because they can receive the benefit sooner and avoid the cost of filing additional paperwork with their taxes. In addition to time value considerations, dealership transfer makes the subsidy effectively refundable, meaning consumers need not have $4,000 of tax liability to take advantage of the full subsidy. The price effect of this policy change is informative of how much consumers value the dealership transfer combined with the change in subsidy "eligibility" based on tax liability.

5.1 Triple-Differences Event Study

This section presents a triple-difference event study comparing cheap and expensive EVs and GVs around the implementation of the tax credit on January 1, 2023 and the policy change on January 1, 2024.

5.1.1 Empirical Strategy

The used vehicles experiencing a price effect as a direct result of the tax credit are characterized by both fuel type and price. Because price is the outcome of interest, we cannot assign treatment groups directly based on transaction price. Instead, we assign treatment status based on a price prediction trained on data prior to the implementation of the tax credit. We use both fuel type and predicted price to construct treatment groups in our triple-difference estimation.

In order to construct the predicted prices, we regress transaction prices on other transaction characteristics and time trends using data from 2022. We define p_{ijyt} as the price of transaction i of vehicle model j and MY y in month t. We include vehicle model by MY fixed effects λ^{jy}, month-of-year fixed effects λ^{m_t}, and dealership fixed effects λ^{d_i}. odo_{ijyt} is the odometer reading of the vehicle in the transaction. We base price predictions on

$$\ln(p_{ijyt}) = \lambda^{jy} + \lambda^{m_t} + \lambda^{d_i} + \beta \cdot odo_{ijyt} + \gamma_y t + \epsilon_{ijyt}. \tag{16}$$

The term $\gamma_y t$ allows for a time trend in prices as a vehicle MY ages and allows this trend to vary by MY. Adding dealership fixed effects accounts for concerns about selection of dealerships into the sample. Fixed

effects for the transaction month capture possible seasonality in transactions. We then take the predicted price as $\hat{p}_{ijyt} = exp(\widehat{ln(p_{ijyt})})$. Appendix D.2 shows the results of the price prediction regression.

We estimate a triple-difference event study of the implementation of the Used Clean Vehicle Credit. The pre-period for the 2023 event contains the months of July through December of 2022, and the post-period begins on January 1, 2023 and extends through July 2023. The pre and post-periods for the 2024 event contain the same months in 2023 and 2024, respectively.

We define G_i as the treatment indicator based on price group for transaction i. $G_i = 1$ if the predicted price is below \$21,000 and $G_i = 0$ if the predicted price is between \$35,000 and \$50,000. EV_j is the treatment indicator based on fuel type, λ^t is the period fixed effect, $\lambda^{make_j} \times \lambda_t$ is an interaction between fixed effects for the make of vehicle j and the month t. We estimate the triple-differences event study graphs using

$$\begin{aligned}\ln(p_{ijyt}) = (G_i \times EV_j \times \lambda^t) + (EV_j \times G_i) + (G_i \times \lambda^t) + (EV_j \times \lambda^t) \\ + (\lambda^{make_j} \times \lambda^t) + \lambda^j + G_i + odo_{ijyt} + \lambda^y + \lambda^{d_i} + \epsilon_{ijyt}. \end{aligned} \tag{17}$$

We include the interaction between vehicle make and time period to account for trends across manufacturers. We cluster standard errors at the model level. The sample includes used vehicle transactions from the Cox data as described in Section 4. We exclude new vehicles because their prices typically respond less to market shocks due to their more elastic supply (Busse, Knittel, and Zettelmeyer 2013).

5.1.2 Results

Figure 2a shows the results for the triple-difference event study around the tax credit implementation at the start of 2023. The tax credit had no statistically significant effect on prices in the short run. Given the effect in log units from the corresponding triple-differences estimation shown in Table A3, we reject price increases of more than \$1,272 for a vehicle that would have cost \$20,000 in the absence of the tax credit with 95 percent confidence.

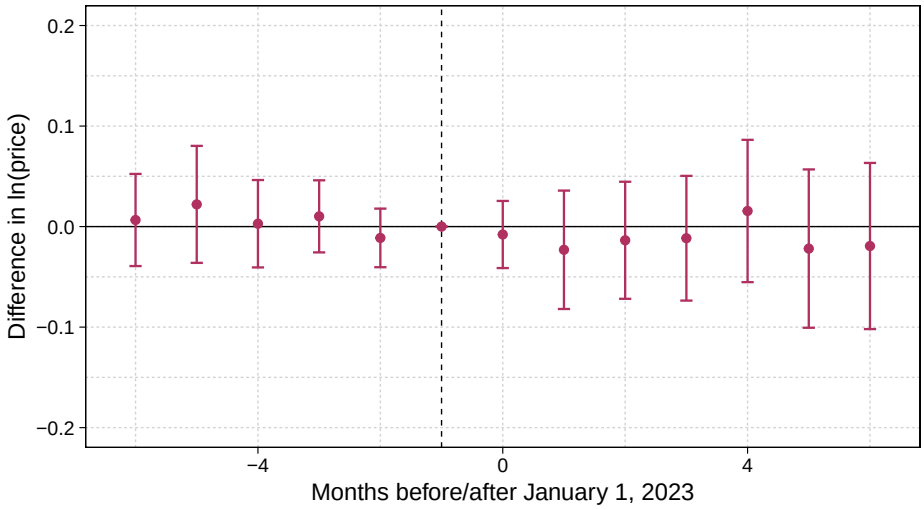
As described in Section 3, several factors could generate these limited effects on prices of eligible EVs. First, the fact that not all buyers are income-eligible dampens any demand effects. Second, the tax credit might have limited effects on demand from credit-eligible consumers because they are not aware of it, because it would be paid in the future, and/or because it is not salient. Awareness and salience could change over time, and in particular might increase at horizons beyond that of our event study.

Using data on new car buyers, we calculate that conditioning on buyers who purchase a vehicle costing under \$26,000, about 49 percent will have a federal tax liability of at least \$4,000. Therefore, μ from our analytical model discussed in Section A is roughly 0.5. This means that the price effects of the subsidy

are attenuated by 50 percent compared to a full eligibility scenario. The full details of our tax liability calculations are discussed in Appendix C.1.

Figure 2: **Price Effect of Used Clean Vehicle Credit on Used EVs**

(a) 2023



(b) 2024

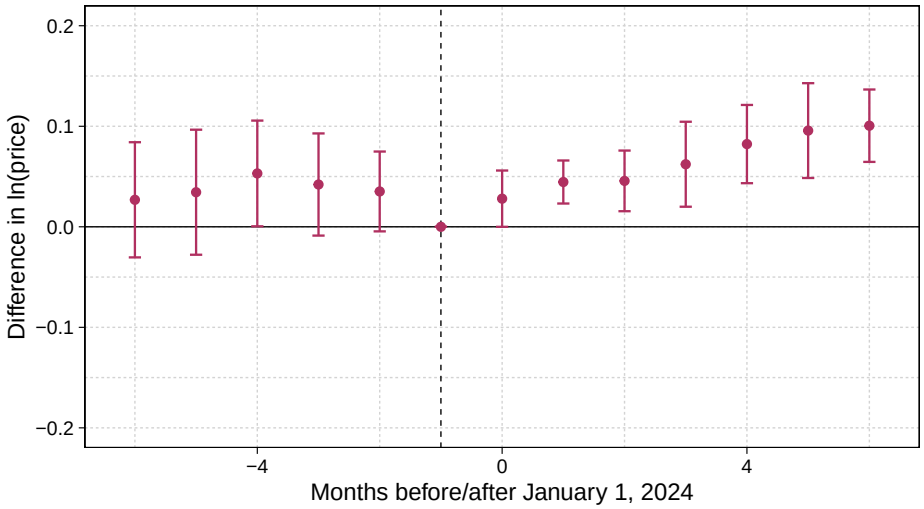


Figure 2b shows the results for the triple-difference event study around the policy change at the start of 2024. We reject price increases of more than $1,665 for a vehicle that would have cost $20,000 in the

absence of the policy change with 95 percent confidence. Importantly, the tax credit is available during the pre-period of the 2024 event. The price effect here is a result of the new availability of a dealership transfer. While the event study shows a gradual price increase throughout the 6 months after January 1, 2024, the price increase in the post period as a whole is not statistically significant as shown in Table A4.

There are several caveats to the interpretation of these results. First, both new and used vehicle markets were very tight in late 2022 before developing more excess supply in 2023, and prices evolved accordingly. Our triple-differences design using the differences between relatively cheap and expensive cars as well as the differences across EVs and GVs makes our event study estimates more credible in terms of handling these market trends. Second, we show the response to these policy changes within the first 6 months, and consumer responses may differ in the long run as discussed above. Third, used GVs and relatively expensive used EVs, the control groups, are affected by changes in the used EV market in equilibrium. We will use a structural model to understand the full equilibrium effects. Fourth, since the January 2023 implementation was not a surprise, in theory there could have been anticipation effects. For example, income-eligible buyers buying vehicles at eligible prices might theoretically have delayed transactions from December 2022 into January 2023. This would generate a selection effect that could affect our estimates. In reality, however, Appendix D.3 shows that there is no evidence of such anticipation effects.

5.2 Bunching Analysis

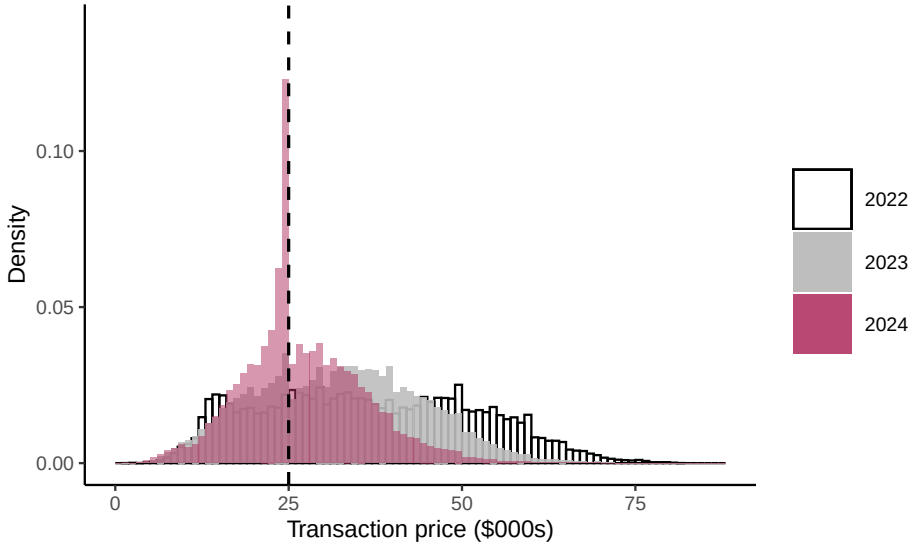
Because of the caveats to our event study results discussed above, we aim to validate our results by looking at the transaction price distributions around the $25,000 price limit.

If the price of eligible used EVs increases as a direct result of the subsidy, prices will increase at most to the price limit because any further increase would remove the subsidy benefit. Given a general price increase of $\$\Delta$, we would expect to see prices bunch at $25,000 because transactions between $\$25,000 - \$\Delta$ and $25,000 in the counterfactual, no-subsidy price distribution would locate at the price limit in the observed distribution. We will use the quantity of this excess mass at $25,000 in the observed distribution to measure the price increase $\$\Delta$. In comparison to the event study analysis, the shape of the price distribution right around $25,000 is far less susceptible to overall market trends and equilibrium effects.

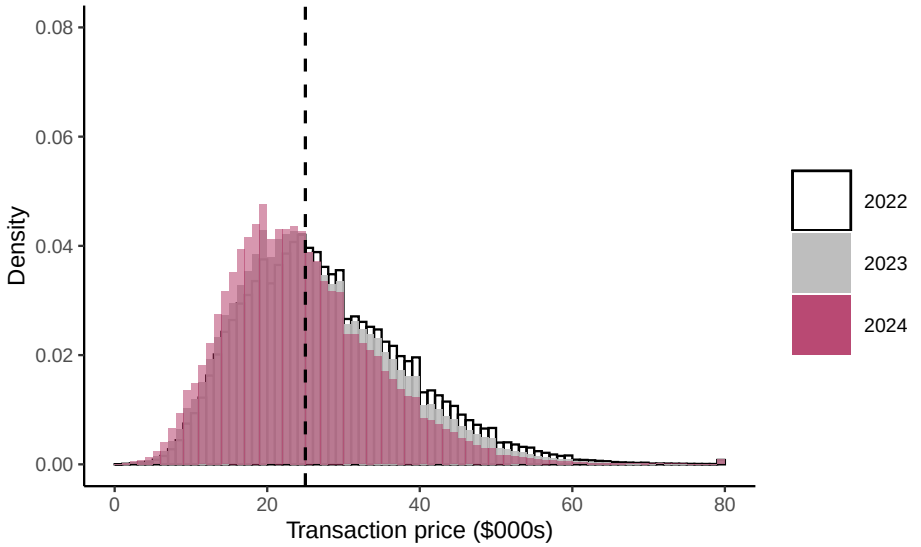
Figure 3 shows the sale price distribution for used vehicle transactions in the Cox Automotive data separated by fuel type and year. We see little evidence of EV prices bunching under $25,000 in 2022, some excess bunching under $25,000 in 2023, and considerably higher excess bunching under $25,000 in 2024. We see no evidence of bunching at $25,000 in the price distribution for GVs, lending support to the claim that this bunching comes from a response to the tax credit. Additional bunching just below the $25,000 price cutoff in 2024 in comparison to 2023 indicates a stronger consumer response to the policy after the introduction of dealership transfers.

Figure 3: **Sale Price Distribution for Used Vehicles**

(a) EVs



(b) GVs

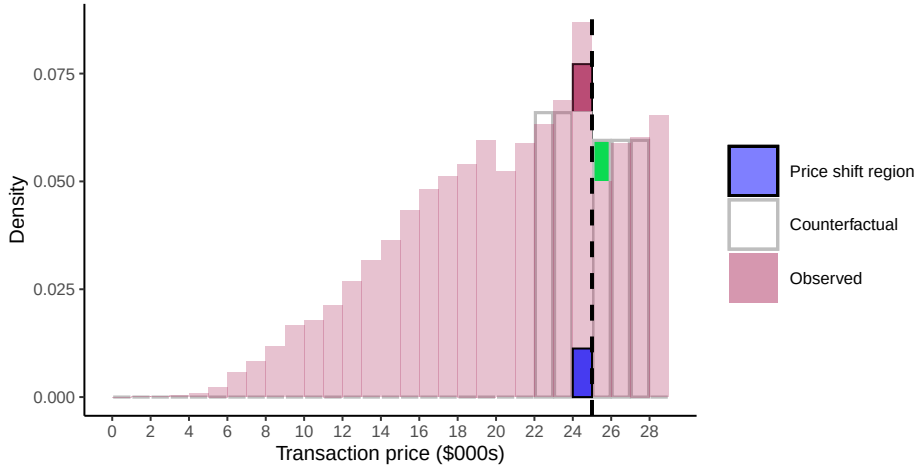


In order to quantify the price shift implied by the bunching patterns we see in the used EV price distributions in 2023 and 2024, we need to develop a measure of the counterfactual distribution around the $25,000 price limit. While the 2022 EV price distribution or the GV price distributions may be a natural candidate for a control group, these distributions exhibit very different patterns that are likely a result of

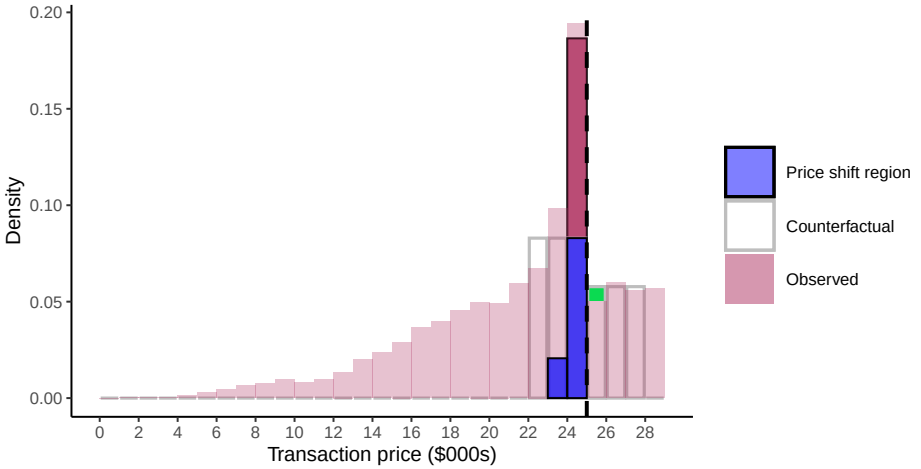
market features outside of the tax credit changes. Instead, we assume that the counterfactual price distribution over $1,000 bins is locally uniform both above and below $25,000. Using $1,000 bins accounts for natural price bunching occurring at certain numbers within $1,000 ranges, and separate distributions above and below $25,000 accounts for the drop-off in the density that can occur after round numbers. The grey bars in Figure 4 show these counterfactual distributions for 2023 and 2024 EVs estimated excluding the bins directly above and below $25,000. The observed distributions in Figure 4 show the price distributions conditional on transactions at or below $29,000.

Figure 4: **Quantification of Price Shift Based on Bunching at $25,000 Price Limit**

(a) 2023



(b) 2024



Now, we can use the counterfactual distribution to quantify the excess mass in the $24,000 to $25,000 region. We do this by subtracting the density in the counterfactual distribution from the observed density. This excess mass may come from both the upward price shift discussed above as well as a downward price shift from directly above $25,000. We may expect this downward price shift in response to the subsidy if car dealerships are maximizing over objectives other than just sale price. For example, the dealerships may sell a car below the counterfactual price to receive the subsidy if this helps to sell the car more quickly.

To isolate the upward price shift, we subtract off the missing mass in the $25,000 to $26,000 bin between the counterfactual and observed distributions, highlighted in green. Then, the highlighted maroon bar shows the excess mass under $25,000 that is a result of the upward price shift. Now, we find the price shift region, highlighted in blue, by finding the region of the counterfactual distribution that must have shifted upwards in order to generate that level of excess mass. The intuition behind this approach is discussed more formally in Appendix B.

We find an upward price shift of $250 in 2023 and $1,282 in 2024. Both of these results lie within the 95 percent confidence region for the price effects found in our event study analyses. These price shift quantities are based on the assumption that transactions are distributed uniformly within each $1,000 bin. Under any other assumptions about the distribution of transactions with the $1,000 price bins, we still find a price shift of greater than $1,000 for EVs in 2024.

We also perform a more standard analysis of the bunching mass based on Kleven and Waseem (2013) in Appendix D.5. This approach fits a counterfactual distribution based on the observed distribution except for a small region around the price limit, while our approach assumes that the entire distribution below the price limit may be shifted. In the analysis in Appendix D.5, the counterfactual distribution represents the same subsidy without a price limit, while our counterfactual of interest here is the distribution with no subsidy. However, it is still useful to validate that a statistically significant excess mass occurs in the standard bunching analysis as well. We find a statistically significant increase in excess mass at $25,000 in the beginning of 2023 and 2024. The bunching mass increased more than doubled by mid-2024 relative to 2023, which implies that dealership transfer had important effects on demand. Finally, to address potential concerns about selection around these events, we show that there is no change in the share of EV transactions through dealerships in either 2023 or 2024 in Appendix D.3.4.

6 Structural Model

In each year t, consumer i makes a static decision to purchase a vehicle j of model year (MY) y and age a from market $m \in \{new, used\}$. All vehicles with age $a = 0$ are sold in market $m = new$. A vehicle j is characterized by the make, body style, and fuel type. Consumer types are characterized by income and the length of time they own a given vehicle. At the end of their holding time, consumers either resell their

vehicle in the used vehicle market or choose to scrap the vehicle. The distinctions between MY y, market m, and age a become relevant as the vehicle ages over the consumer's holding time.

In the new vehicle market, supply is determined by new vehicle prices set by profit-maximizing automakers. In the used vehicle market, supply is determined by (1) the number of consumers holding each vehicle type that reach the end of their holding time in period t, net of the scrapped vehicles, and (2) the number of used vehicles transferred from institutions, including government and rental car companies, to individuals. New vehicle prices are determined by automakers to maximize their profits, while used vehicle prices are set to clear the market.

6.1 Vehicle Demand

Consumer i is defined by income inc_i, holding time h_i, and unobserved attributes $\boldsymbol{\nu}_i$. Let v_{ijmya} denote the utility of consumer i from owning vehicle j purchased from market m with MY y and age a for one period. Because consumer i expects to resell or scrap the vehicle at the end of the holding time, consumer i's utility of purchasing vehicle j of age a in is given by

$$U_{ijmya} = \sum_{k=0}^{h_i-1} v_{ijmya+k} + \alpha_i \Big(p_{jya} - \rho^{h_i} [1 - g(\cdot)] \, \widetilde{p}_{jya+h_i} \Big) \tag{18}$$

where α_i gives the consumer disutility over prices, ρ is the real interest rate, $g(\cdot)$ is the probability of scrappage, and $\widetilde{p}_{jya+h_i}$ is the expected resale price at the end of the holding period. $\rho^{h_i}[1 - g(\cdot)] \, \widetilde{p}_{jya+h_i}$ captures the expected future benefit of reselling the vehicle assuming scrap values of zero.

We parameterize the one-period utility v_{ijmya} as

$$v_{ijmya} = X_{jm}\boldsymbol{\beta}_i + \beta_i^a a + \xi_{jmy} + \varepsilon_{ijmy} \tag{19}$$

where X_{jm} is a vector of vehicle-market characteristics, β_i^a is the age disutility parameter, ξ_{jmy} is the unobserved quality, and ε_{ijmy} is an idiosyncratic preference shock with a type I extreme value distribution. $X_{jm}\boldsymbol{\beta}_i$, ξ_{jmy}, and ε_{ijmy} do not depend on age and so remain constant over the holding period. Because of this, we can write the utility in the second period of the holding time as $v_{ijmya+1} = v_{ijmya} + \beta_i^a$, which is equivalent to the utility of holding the vehicle in the first period plus the additional disutility from the vehicle aging by one year.

We assume that consumers are forward-looking and so the expected price is the same as the future equilibrium prices: $\widetilde{p}_{jya+h_i} = p_{jya+h_i}$. We can now define the average per-period individual utility as

$$\begin{aligned} u_{ijmya} &= v_{ijmya} + \frac{1}{h_i} \left[\sum_{k=1}^{h_i-1} \beta_i^a k + \alpha_i \Big(p_{jya} - \rho^{h_i} [1 - g(\cdot)] p_{jya+h_i} \Big) \right] \\ &= \alpha_i \frac{1}{h_i} \Big(p_{jya} - \rho^{h_i} [1 - g(\cdot)] p_{jya+h_i} \Big) + X_{jm}\beta_i + \beta_i^a (a + \frac{h_i - 1}{2}) + \xi_{jmy} + \varepsilon_{ijmy} \end{aligned} \tag{20}$$

Consumers make purchase decisions to maximize their average per-period utility, which is equivalent to maximizing their total utility. In this setup, the impact of consumer preferences over new vehicles, vehicle age, and expected resale value on choice probabilities will depend on consumer holding time.

6.1.1 Scrappage Decision

We assume that the consumer scrap decision is model-specific and depends on the resale price p_{jya} and vehicle age. A consumer is less likely to scrap a vehicle when the resale price is higher. Following Bento et al. (2009), we set the scrap rate at the end of the holding period as

$$g_{ja}(p) = \zeta_{ja} \cdot (p)^{\eta_p} \tag{21}$$

where η_p represents the price elasticity of the scrap probability. Conditional on resale price, the scrap rate depends on age but does not depend on the vehicle MY.

6.2 Supply of New Vehicles

The supply of new vehicles depends on new vehicle prices, which are set by automakers. Vehicle producer f chooses new vehicle prices $\{p_{jya} | a = 0,\ j \in J_{ft}\}$, where J_{ft} is the product offerings by firm f in period t, to maximize its profit:

$$\pi_{ft} = \max_{\{p_{jya} | a=0,\ j \in J_{ft}\}} \sum_{j \in J_{ft}} (p_{jy0} - mc_j)\ Q(\boldsymbol{p}_{a=0,t},\ \boldsymbol{p}_{a>0,t},\ \boldsymbol{q}_{a>0,t}) \tag{22}$$

where $\boldsymbol{p}_{a=0,t}$ and $\boldsymbol{p}_{a>0,t}$ are the vectors of prices for the new and used vehicles, respectively, available in the market in period t and $\boldsymbol{q}_{a>0,t}$ is the supply of used vehicles in period T.

6.3 Supply of Used Vehicles

For each model j, we have the following ownership matrix, which counts the number of owners intending to sell their vehicle in the upcoming year, two years later, three years later, and so forth, up to T years in the future. We call this matrix a consumer ownership matrix (COM), which summarizes the ownership structure of model j in a period.

$$\Omega^j = \begin{pmatrix} \Omega^j_{11} & \Omega^j_{1,2} & \dots & \Omega^j_{1,T-2} & \Omega^j_{1,T-1} & \Omega^j_{1,T} \\ \Omega^j_{21} & \Omega^j_{2,2} & \dots & \Omega^j_{2,T-2} & \Omega^j_{2,T-1} & 0 \\ \Omega^j_{31} & \Omega^j_{3,2} & \dots & \Omega^j_{3,T-2} & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ \Omega^j_{T-1,1} & \Omega^j_{T-1,2} & \dots & 0 & 0 & 0 \\ \Omega^j_{T,1} & 0 & \dots & 0 & 0 & 0 \end{pmatrix}$$

Ω^j_{at} represents the number of model j owners with an age of a who intend to sell their cars in t years. As all vehicles with an age of T will be scrapped at the conclusion of each period, Ω^j_{at} equates to zero if $a+t$ exceeds $T+1$. In the COM, the diagonal elements, denoted as Ω^j_{at} whose $a+t=T+1$, represent the number of model j's that will be owned by the current owner until they are scrapped.

The supply of used cars in period t consists of the total number of vehicles whose ownership ended in the previous period $(t-1)$, combined with the net transfer of vehicles from institutions such as government agencies and rental car companies. The first column of COM and scrap probabilities determines the supply of used vehicles by individual owners for model j in the subsequent period. Specifically, the supply of model j by individual owners with age a in the next period is given by $\Omega^j_{a1} \times [1 - g_{ja}(\boldsymbol{p})]$. We take institutions' new vehicle purchases as exogenous. Supply of used vehicles from institutions varies over time based on the institutions' new vehicle purchases, which are fixed, and their pre-existing vehicle stock across models and ages.

6.3.1 Update Rule of COM

A next period COM is determined by car owners and buyers in the current period:

R1) **Owners who did not sell their cars at the end of the last period**

$$\Omega^j = \begin{pmatrix} \Omega^j_{11} & \Omega^j_{1,2} & \cdots & \Omega^j_{1,T-2} & \Omega^j_{1,T-1} & \Omega^j_{1,T} \\ \Omega^j_{21} & \Omega^j_{2,2} & \cdots & \Omega^j_{2,T-2} & \Omega^j_{2,T-1} & 0 \\ \Omega^j_{31} & \Omega^j_{3,2} & \cdots & \Omega^j_{3,T-2} & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ \Omega^j_{T-1,1} & \Omega^j_{T-1,2} & \cdots & 0 & 0 & 0 \\ \Omega^j_{T,1} & 0 & \cdots & 0 & 0 & 0 \end{pmatrix}$$

The green-shaded area represents the number of owners who did not sell their vehicles. These numbers will be shifted to the red-shaded area.

R2) **New and used car buyers**

First, new vehicle buyers fill the first row of the new COM. For instance, the count of consumers with a fixed holding time of 6 years will be $\Omega^j_{1,6}$.

Second, used car buyers add to the second through the last rows of the new COM. The values in the first column of the previous COM, adjusted by one minus the scrap probabilities, are redistributed into the red-shaded area of the new COM. Specifically, the number of consumers of product j with age a, holding time t years is added to $\Omega_{a,t}$ in the new COM.

These are the basic update rules for the COM. With the used EV credit policy, we divide products into those with and without used EV credits and update two COMs for one model j: COMs with credits and without credits.

7 Estimation

7.1 Scrap Probability

The yearly scrap rate of a vehicle j at age a is given by

$$r_{jat} = \frac{N_{jat} - N_{ja+1,t+1}}{N_{jat}} \tag{23}$$

where N_{jat} is the total stock of model j aged a in period t. For consumer choices, the relevant scrap rate is not the overall scrap rate between any two periods but rather the probability of scrapping the vehicle conditional on the owner reaching the end of the holding time. The overall scrap rate underestimates this probability because many of the vehicles that remain in the stock across both years are held by the same owner within their holding period.

We define g_{jat} as the scrap rate associated with car owners' scrap decisions, which occur right before the end of their holding period. Let n_{jat} be the number of vehicle j with age a that reach the end of the current owner's holding time in period t and could potentially be traded in the next period. Then,

$$g_{jat} n_{jat} = N_{jat} - N_{ja+1,t+1} = r_{jat} N_{jat} \tag{24}$$

where $N_{jat} - N_{ja+1,t+1}$ is the number of scrapped vehicles. Since we observe all the values in Equation (24) except for g_{jat}, we can calculate the scrap probabilities after the holding period. Using the computed g_{jat}, we estimate a scrap function, which is specified as follows:

$$\begin{aligned} g_{jat} &= exp(\zeta_j + \eta_a a + \epsilon_{jat}) \cdot (p_{ja})^{\eta_p} \\ \Rightarrow\ ln(g_{jat}) &= \zeta_j + \eta_a a + \eta_p ln(p_{ja}) + \varepsilon_{jat} \end{aligned} \tag{25}$$

where ζ_j represents the model fixed effects, η_a determines the age elasticity of scrap rates, and η_p denotes the price elasticity, which will be either calibrated or estimated.

The first column of Table 3 presents the OLS estimates of the scrap parameters. However, there is an endogeneity issue in this regression specification as the price p_{jat} is likely correlated with the scrappage shock ϵ_{jat}. Thus, for our main specification, we calibrate the price elasticity of scrap rates to $\eta_p = -0.7$ from Jacobsen and Benthem (2015).[8] We estimate the remaining parameters for our main specification as

[8] Jacobsen and Benthem (2015) use the yearly scrap rates r_{jat} instead of the scrap rates after holding periods. However, Equation (24) shows that the price elasticity of scrap rates is identical for both cases

$$\frac{dln(r_{jat})}{dln(p_{jat})} = \frac{dln(g_{jat})}{dln(p_{jat})} = \eta_p \tag{26}$$

Table 3: **Scrap Parameter Estimation**

	(1) $\ln(g_{jat})$	(2) $\ln(g_{jat})$ + 0.7 ln(price)
Age	−0.003	0.073
	(0.022)	(0.004)
ln(price)	−1.405	
	(0.199)	
Model FEs	Yes	Yes
Observations	1,652	1,652

shown in column 2.

7.2 Demand Parameters

From our utility specification in Equation 20 in Section 6.1, we define a linear utility over vehicle types with heterogeneous preferences over rent, fuel type, age, and new vehicles. We estimate

$$\begin{aligned} u_{ijmya} &= \beta_0 + \lambda_j + \beta_i^{EV} EV_j + \beta_i^m \mathbb{1}\{m = new\} + \beta_i^a \left(a + \frac{h_i - 1}{2}\right) + \alpha_i \ln(P_{ijya}) + \xi_{jmy} + \varepsilon_{ijmy} \\ &= \delta_{jmy} + \beta^a \left(a + \frac{h_i - 1}{2}\right) + \boldsymbol{\beta}_i X_{ijma} + \alpha_i \ln(P_{ijya}) + \varepsilon_{ijmy} \end{aligned} \tag{27}$$

where λ_j is the vehicle type fixed effect, EV_j is an indicator which equals 1 if vehicle j is an EV, inc_i is the simulated income of consumer i, and $P_{ijya} = \frac{1}{h_i}(p_{jya} - \rho^{h_i}[1 - g(\cdot)]p_{jya+h_i})$ captures the average per-period payment. We discuss the consumer holding time distribution in Appendix E.1 and estimation of future prices in Appendix E.2.

We parameterize $\boldsymbol{\beta}_i$ and α_i as

$$\boldsymbol{\beta}_i = \boldsymbol{\sigma}\boldsymbol{\nu}_i + \boldsymbol{\beta}^{inc}\mathbb{1}\{inc_i > \$75k\} \quad , \quad \alpha_i = \alpha^{high}\mathbb{1}\{inc_i > \$75k\} + \alpha^{low}\mathbb{1}\{inc_i \leq \$75k\},$$

so we can estimate important preferences for high and low-income groups separately. $X_{ijma} = \{EV_j, a + \frac{h_i - 1}{2}, \mathbb{1}\{m = new\}\}$ is a vector of vehicle-age-market characteristics. $\boldsymbol{\nu}_i = \{\nu_i^{EV}, \nu_i^a, \nu_i^m\}$ is a vector of unobserved consumer preferences. The preference over EVs is drawn from a standard normal distribution and the preferences over new vehicles and vehicle age are drawn from a log normal distribution. We set $\rho = 0.95$ and use the scrappage parameters from 7.1 to compute the average per-period payment P_{ijya}.

We estimate α_i, β^a, $\boldsymbol{\beta}^{inc} = \{\beta^{inc,EV}, \beta^{inc,a}, \beta^{inc,m}\}$, and $\boldsymbol{\sigma} = \{\sigma^{EV}, \sigma^a, \sigma^m\}$ using a just-identified generalized method of moments (GMM). The set of moments are discussed in detail in Appendix E.3. To compute the target moments, we use the observed second choice shares from Strategic Vision and demographic data from both Strategic Vision and the NHTS. We match the price elasticity of EVs in aggregate to -2.1, the price elasticity of demand for EVs found from quasi-experimental variation in EV subsidies in California in Muehlegger and Rapson (2022).

We follow Berry, Levinsohn, and Pakes (1995) to recover the mean utilities δ_{jy} by matching the observed and model-predicted market shares of vehicles. We regress the implied mean utilities on the vector of vehicle characteristics to estimate the remaining utility parameters.

7.2.1 Results

Table 4 shows the estimation results. We find that α^{low} is greater than α^{high}, indicating that low-income consumers are relatively more price elastic. σ_a and β_a are both negative, corresponding with additional disutility as a vehicle ages. Based on $\boldsymbol{\beta}^{inc}$, we see that high-income consumers have a relatively high utility from new vehicles and EVs. These relative preferences will be important to the distributional consequences of the EV subsidies.

Table 4: **Estimated Demand Parameters**

α^{low}	7.511	(1.365)
α^{high}	4.311	(0.225)
σ_{EV}	3.464	(0.523)
σ_a	-0.045	(0.010)
σ_{new}	-0.492	(0.938)
β_a	-0.786	(0.214)
$\beta_{inc,ev}$	24.216	(0.056)
$\beta_{inc,new}$	0.387	(0.097)
$\beta_{inc,age}$	0.372	(0.236)
β_{new}	1.091	(0.087)
β_0	33.539	(0.182)
Model FE	Yes	

7.3 Exogenous Supply of Used Cars from Institutions

The supply of used vehicles from institutions is determined by four key factors: (1) new vehicle purchases by institutions, (2) institutional vehicle stocks at the beginning of the simulation period, (3) annual scrap rates of institutional vehicles, and (4) the percentage of vehicles transferred from institutional stocks to individuals.

First, new vehicle purchases by institutions are calibrated at the model level based on institutional vehicle purchases between October 2022 and September 2023. We assume that institutional purchases of new vehicles remain fixed throughout the simulation periods. Second, institutional stocks are determined using vehicle stock data as of the end of Q3 2023, which serves as the starting point for the simulation. Institutional stocks vary over time due to new purchases, aging, and scrappage. Third, annual scrap rates for institutional vehicles are computed at the car type by MY level. These rates are calibrated by comparing total vehicle stocks, including both individual and institutional vehicles, between Q3 2022 and Q3 2023. The scrap rates are fixed and not influenced by endogenous prices.

Lastly, the percentage of vehicles transferred from institutions to individuals is fixed at the car type by MY level. This transfer rate is calibrated by comparing net transfers from institutions to individuals with institutional vehicle stocks. The following equation is used to calculate the net transfer of used vehicles:

$$\begin{aligned} \text{2023 individual stock} = \text{2022 individual stock} &- \text{individual scrappage} \\ &+ \text{individual purchases of new vehicles} \\ &+ \text{used vehicle net transfer from institutions} \end{aligned}$$

This methodology provides the exogenous supply of used vehicles from institutions for each year of the simulation period. Importantly, the calibration of annual institutional scrap rates and transfer rates is conducted at the car type by MY level, rather than the model level. This choice stems from the incomplete range of MYs for many models, which prevents reliable calibration of scrap and transfer rates across the full vehicle age range. Despite this, model-level data on new vehicle purchases and institutional stocks introduces significant variation in institutional transfers of used vehicles.

8 Counterfactual Equilibrium Simulation

8.1 Used EV Tax Credit

Several features of this policy introduce complexity into the equilibrium analysis. First, EVs are categorized into two types: those traded after the policy introduction and those not yet traded. The former are ineligible for used EV credits. These EVs, with and without credits, must be counted separately in two distinct COMs

for each model j. We denote the COM for EV model j that has not traded post-policy as Ω^j, while $\widetilde{\Omega}^j$ counts the number of model j units without available used credits. Second, the one-time nature of the used EV credits makes the equilibrium non-stationary. In the year of the policy introduction, the elements of $\widetilde{\Omega}^j$ are all zeros. Over time, the elements in Ω^j decrease, while $\widetilde{\Omega}^j$ increases.

An EV with an available credit has a higher value, and we refer to the price gap between the same EV model at the same age, based on the availability of used EV credits, as a credit premium. This premium is positive but cannot exceed the value of the used EV credit, which is \$4,000. It is determined by both the demand and supply of used EVs. For instance, if there are many used EVs not traded after the policy introduction in the market, then premiums are lower, while if there are many used EVs without remaining credits, then premiums become higher.

If a higher proportion of used vehicle transactions are eligible for the credit, the premium tends to be higher. For example, a 3-year-old Tesla Model X, with a new price exceeding \$100,000, is likely to have a relatively low used credit premium. Potential buyers are typically households with incomes above the IRA threshold. With fewer potential eligible buyers, the pass-through rate of the consumer tax credit to the sellers should correspondingly be lower. Moreover, it may take several years for its price to fall below \$25,000, making it eligible for the credit, and thus a greater time discount should be applied.

8.2 Equilibrium Concept

The new equilibrium is simulated by stacking a set of short-run equilibria, similar to Bento et al. (2009). In one short-run (single-period) equilibrium, given consumers' beliefs over future resale prices and future scrap probabilities, the set of equilibrium prices should satisfy the following conditions:

1) **New vehicle prices**: satisfy the profit maximization conditions of automakers

2) **Used vehicle prices**: clear the used vehicle markets across different models and ages

3) **Used EV credit premiums**: clear the used vehicle markets within the same models and ages, differentiating between vehicles with and without available credits.

Here, the used vehicle supplies are determined by the previous COMs and the scrap probabilities. The scrap probabilities are endogenous and depend on the current period vehicle prices (plus credit premiums for EVs not traded before). After we compute the equilibrium in period t, we update the COM according to the rules explained in Section 6.3.1. Then, we repeat the process of simulating a short-run equilibrium until we have the full set of equilibria over the simulation periods.

For the forward-looking consumer, rent depends over consumers' expectations of future equilibrium prices and premiums. We assume consumers are rational, so the anticipated future prices and premiums align with the actual equilibrium prices and premiums realized in the future. However, this requires knowledge of

future equilibrium prices, which depend on even further future prices. Thus, it is necessary to define a final period after which equilibrium prices and premiums remain constant.

We assume that equilibrium prices and premiums stabilize after $T = 20$ periods (i.e., from 2043 onward). After T periods, consumers face a consistent set of model-by-age combinations. By that time, all vehicle ages are available for every model in the market, including those introduced in 2023. In 2023, only new vehicles (age zero) are available for these models, but T periods later, all ages from zero to 19 are in the market. Furthermore, discontinued models—those without age-zero vehicles in 2023—will have disappeared from consumers' choice sets by T periods later. We assume consumers expect this unchanging set of model-by-age combinations to have stable prices that remain constant thereafter.

8.3 Equilibrium Simulation Steps

We begin with initial consumers' expectations of future prices and premiums for the second, the third, and so on, up to the T-th simulation year. Using these expectations, we calculate equilibrium prices and premiums over T years, as outlined below.

1. For simulation year t, given the credit premiums, search for the used car prices p_{jat} for $a > 0$ such that

$$D_{jat} + \widetilde{D}_{jat} = (1 - g_{jat}) \cdot \Omega_{a1}^{jt} + (1 - \widetilde{g}_{jat}) \cdot \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a > 0 \tag{28}$$

   and for the new car prices that satisfy the first-order conditions of firms' profit maximization.

1. Given car prices p_{j0t} search for the credit premiums l_{jat} that satisfy the following conditions:

$$D_{jat} : \widetilde{D}_{jat} = (1 - g_{jat}) \cdot \Omega_{a1}^{jt} : (1 - \widetilde{g}_{jat}) \cdot \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a \tag{29}$$

   where D represents the demand for vehicles with a used EV credit, and $\widetilde{D}$ denotes the demand for EVs without a credit. g_{jat} and $\widetilde{g}_{jat}$ are the scrap rates with and without credits, respectively. Both demand and scrap rates depend on the equilibrium prices and premiums.

3. Repeat Steps 1-2 until prices and premiums in the simulation year t satisfy firms' profit maximization conditions and used car market clearing conditions.

4. Update COMs for the next period using the current equilibrium prices, scrap rates, and transactions.

5. Repeat Steps 1-4 for T times to find find all equilibria across the T simulation periods

6. Update consumers' beliefs with the realized equilibrium prices and premiums. Iterate the entire process until consumers' beliefs converge to the actual equilibrium prices and premiums.

8.4 Steady-State Simulation

To achieve the steady state, we iteratively: (1) calculate the equilibrium prices and premiums for the T-th simulation year, (2) update the COMs, and (3) update consumer expectations, as outlined in the previous subsections, until the equilibrium prices stabilize. At this point, consumers expect future prices and premiums to match the current equilibrium prices and premiums. Furthermore, the set of available model-by-age combinations remains unchanged beyond the T-th year. Thus, when both the equilibrium prices and consumer expectations no longer change, the system is considered to have reached a steady state.

9 Simulation Results

An important next step is to examine the conditions under which subsidies for new and used EVs lead to distinct outcomes in both the short and long run. As discussed in Section 3.2, subsidies for new and used EVs result in identical steady-state equilibrium outcomes when vehicle scrap rates are exogenous (i.e., unaffected by prices).[9] However, there are several factors that lead to different outcomes from new and used EV subsidies. Understanding these differences is critical for assessing the relative efficiency and distributional consequences of new and used EV subsidies. We identify four primary reasons why real-world effects diverge from the simple steady-state case discussed in Section 3.3.1:

Endogenous vehicle scrappage The scrap rates of used vehicles depend on vehicle prices, so the supply is not perfectly inelastic. Thus, the effects on the vehicle stock composition will differ across new and used subsidies. New EV subsidies would lower used EV prices by shifting demand from used to new EVs, which could accelerate the scrappage of used EVs. In contrast, used EV subsidies would reduce the number of scrapped EVs, retaining more vehicles in the stock.

If scrap rates are inelastic, used EV subsidies have only a positive impact on new EV demand because they raise the resale value for new EV buyers. However, if scrap rates depend on prices, used EV subsidies increase the used EV stock, which will steal demand from new EVs, also creating negative impacts on new EV demand. The stronger the substitution between new and used EVs, the greater this negative impact on new EV demand and prices will be. Moreover, new and used EV subsidies will reduce the GV stock through two channels. First, they will decrease new GV sales, slowing the accumulation of GV stock. Second, they will lower used GV prices, accelerating the scrappage of used GVs. Depending on the substitution patterns among new EVs, used EVs, new GVs, and used GVs, the relative effectiveness of new versus used EV subsidies in reducing GV stock will differ.

[9] We will later verify this equivalence using counterfactual simulations with the estimated structural model.

Vehicle stock accumulation Increased sales of new vehicles do not immediately result in a larger stock of used EVs because vehicle stock accumulation takes place over many years. This delay limits the short-term effects of new EV subsidies on the supply of used EVs, their prices, and the benefits to used EV buyers, particularly low-income households.

One-time feature of used EV subsidies Already-traded EVs are no longer eligible for used EV subsidies. As a result, the prices of EVs eligible for subsidies increase, while the prices of EVs without credits (already traded) decrease with the policy intervention. Consequently, the scrappage rates of used EVs without credits would increase with the used EV subsidies. This dynamic leads to fewer EVs being scrapped before they are traded but then higher scrappage rates after they have been traded.

Income and price limits for used EV subsidies Used EV subsidies under the IRA are available only for transactions involving EVs priced below $25,000, creating different effects on new EV prices for cheap and expensive vehicles. Expensive EVs take longer to depreciate below the cutoff and have fewer eligible buyers, as many potential buyers exceed the income threshold for subsidy eligibility. This results in a lower credit premium, limiting the impact of used EV subsidies on the resale values of new EV buyers, particularly for higher-priced models.

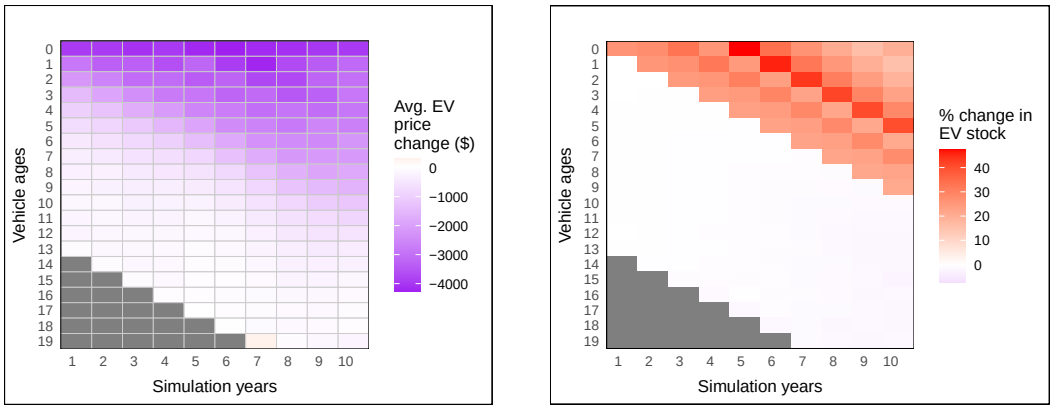
9.1 Equilibrium Outcomes [Preliminary]

In this section, we present equilibrium outcomes under four counterfactual policy scenarios. The first scenario introduces a $4,000 subsidy for new EVs with no eligibility conditions, and the second instead includes a $4,000 subsidy for used EVs with no eligibility restrictions. The third provides a $4,000 subsidy for used EVs, limited to buyers with an income below $75,000. The fourth scenario adds a vehicle price limit of $25,000. Consistent with the used EV tax credit in the IRA, the simulated used EV subsidies are one-time incentives, meaning that a used EV becomes ineligible for future subsidies once sold after the policy introduction. The fourth policy scenario is designed to closely replicate this policy, capturing its key eligibility criteria.

9.1.1 Impact of new EV subsidies

Figure 5 illustrates the changes in EV stocks and prices compared to a baseline scenario with no subsidy. Each row represents vehicle age, ranging from new (age 0) to 19 years old, while each column corresponds to the 10 simulation years from 2024 to 2033. The oldest EV in 2024 is 13 years old, so the gray-shaded area indicates age ranges where no EVs exist. Figure 5a shows the change in total EV stock at each age relative to the baseline and Figure 5b shows the change in the average EV price (i.e., consumer price after subsidy)

Figure 5: Effects of New EV Subsidies on EV Prices and Stocks



(a) Effective EV Prices

(b) EV Stocks

relative to the baseline. The new EV subsidy directly reduces the effective price of new EVs, resulting in increased new EV sales as predicted by the analytical model. The subsidy incidence primarily benefits EV buyers, with consumer prices for new EVs decreasing by nearly $4,000. In addition, prices for used EVs begin to decline as the EV stocks from past new vehicle purchases age.

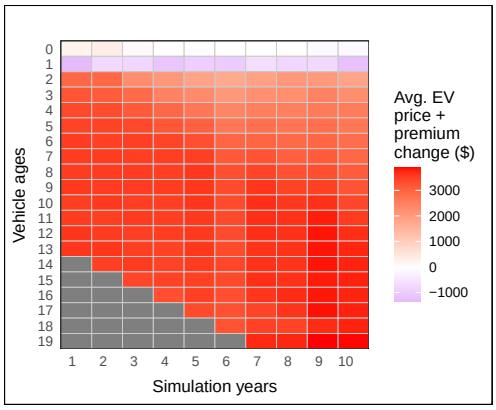
However, unlike the steady-state assumption in the analytical model, an increase in new EV sales does not immediately translate into a rise in the stock of older used EVs. Accumulating used EVs takes time, so the increase in new EV sales does not instantly lead to lower prices across all used EV age groups. This gradual accumulation process breaks the steady-state equivalence between new and used subsidies. In the short run, the new EV subsidy even reduces the stock of older used EVs by lowering their prices and accelerating scrappage. Although younger used EV stock grows gradually, the total used EV stock will only begin to recover after sufficient time for stock accumulation.

9.1.2 Impact of used EV subsidies

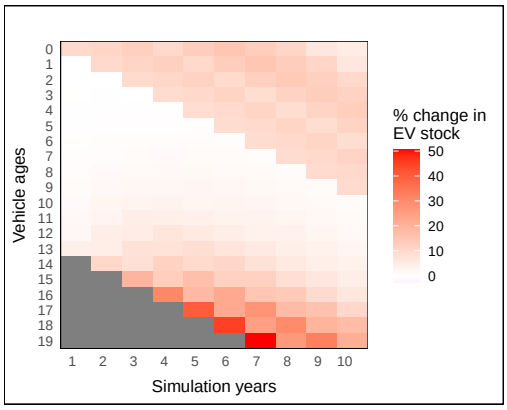
Figure 6 illustrates the quantity and price effects of used EV subsidies across three scenarios: (i) no eligibility conditions, (ii) a $75,000 income limit, and (iii) both income and $25,000 price limits. These figures present the the changes in average EV seller prices and in EV stocks compared to a no-subsidy baseline. Across all scenarios, prices of older EVs and EV stocks generally increase. This effect on EV stocks is strongest for very old EVs, where the reduction in scrappage induced by higher selling prices is most influential. We also see some increases in younger EV stocks as new EV purchases are induced through the likelihood of a higher resale price. As discussed above, the changes in EV stocks take time to accumulate.

We discuss results for additional outcomes in Appendix F.

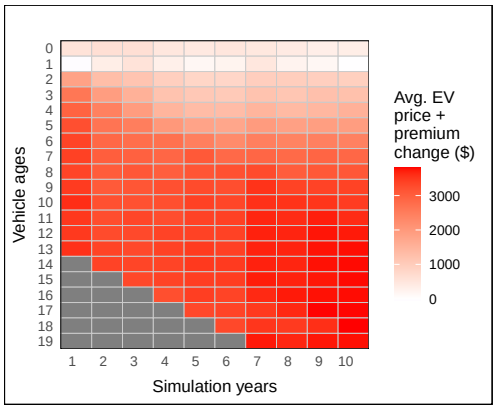
Figure 6: Effects of New EV Subsidies on EV Prices and Stocks



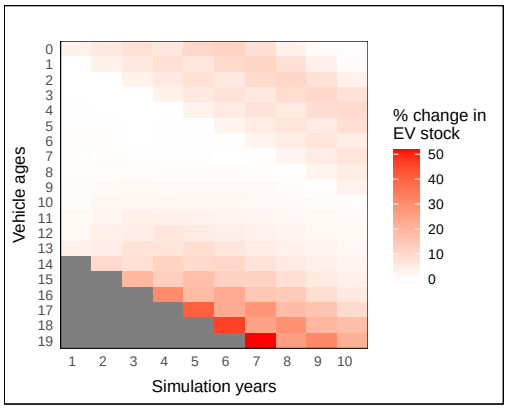
(a) EV Prices - Scenario (i)



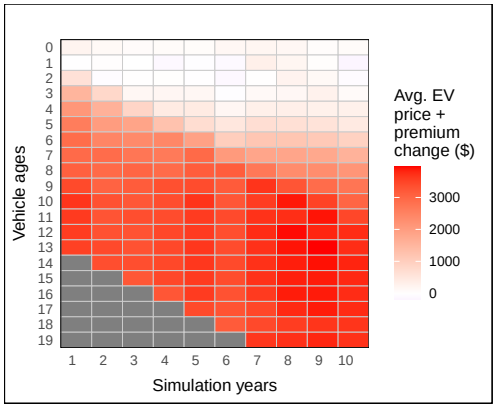
(b) EV Stocks - Scenario (i)



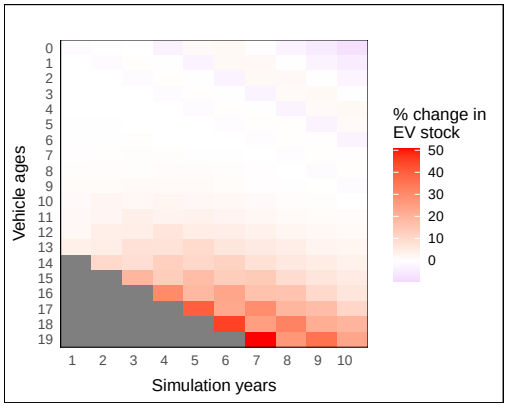
(c) EV Prices - Scenario (ii)



(d) EV Stocks - Scenario (ii)



(e) EV Prices - Scenario (iii)



(f) EV Stocks - Scenario (iii)

9.2 Market Statistics and Welfare Effects

In this section we describe the equilibrium market outcomes and welfare effects under each policy scenario from our counterfactual simulations.

In Panel A of Table 5, we show the EV registration share, new EV sales share, and sales-weighted average prices for new and used EVs. We provide these statistics in years one and ten to better illustrate the short and long-term effects of the policies. Columns 1-5 display these statistics for the no subsidy, new subsidy, used subsidy, used subsidy with income limits, and used subsidy with income and price limits scenarios, respectively.

We see that the new subsidy immediately raises the new EV market share. As the simulation progresses, these vehicles are eventually resold into the used market. This extra used supply depresses used EV prices by year 10, which then attenuates the new EV sales share by year ten. However, the overall EV registration share is highest in this scenario.

The direction of the effects across outcomes are the same for all the used EV subsidy scenarios. The average used EV prices and new EV sales shares are immediately higher than the baseline in year 1 and decrease as the new EVs transition to used EV supply by year ten. As expected, the size of the effects become smaller as more eligibility requirements are added.

We also present the welfare effects of each scenario compared to the no-subsidy baseline in Panel B of Table 5. All quantities are per dollar of government expenditure. We discuss four components of welfare: consumer surplus, vehicle manufacturers' profit, vehicle externalities, and government expenditure. As a key policy goal of used subsidies is equity, we calculate consumer surplus separately for consumers with income above and below $75,000. Profits and externalities are reported separately for EVs and GVs. We describe our calculation of externalities in Appendix C.2.

As expected, we find that EV subsidies generally increase EV manufacturer profits and decrease externalities. The largest reduction in externalities comes from the new vehicle subsidies, but these also lead to the largest reduction in consumer surplus for low-income consumers. This result highlights the potential trade-off between equity and efficiency in environmental policy design.

Table 5: **Market Statistics and Welfare Effects from Simulated Policies**

	(1) No subsidy	(2) New subsidy	(3) Used subsidy	(4) Used subsidy + income limit	(5) Used subsidy + inc & price limit
Panel A: Market Statistics					
Year 1					
EV registrations share (%)	2.07	2.18	2.12	2.10	2.08
New EV sales share (%)	10.12	13.12	11.32	10.53	10.15
New EV avg price ('000s)	60.72	60.72	60.97	61.27	60.95
Used EV avg price ('000s)	32.94	31.32	34.85	34.56	33.50
Year 10					
EV registrations share (%)	5.16	6.31	5.65	5.51	5.24
New EV sales share (%)	7.07	8.36	8.05	7.81	6.98
New EV avg price ('000s)	58.72	58.51	58.62	59.07	58.80
Used EV avg price ('000s)	29.75	26.66	32.19	31.97	30.96
Panel B: Welfare Relative to No Subsidy Per $1 Gov't Expenditure					
ΔCS	-	-0.24	0.24	0.34	1.56
ΔCS with inc $\leq$ \$75k	-	-0.39	-0.09	0.40	1.13
ΔCS with inc $\geq$ \$75k	-	0.15	0.33	-0.06	0.43
ΔProfit	-	-0.21	-0.05	0.39	0.35
ΔGV profit	-	-0.42	-0.26	0.00	0.23
ΔEV profit	-	0.20	0.21	0.39	0.12
ΔExternality	-	0.14	0.08	0.09	0.39
ΔGV externality	-	0.56	0.40	0.34	0.54
ΔEV externality	-	-0.42	-0.31	-0.25	-0.15
ΔCS + Δprofit + Δexternality	-	-0.32	0.27	0.82	2.30
ΔGov't expenditure	-	1.00	1.00	1.00	1.00

Notes: Average prices are sales-weighted. Panel B is the values summed across the ten years of the simulation. A negative value of externality reflects a negative externality, and vice versa.

10 Conclusion

In this paper, we study the efficiency and distributional effects of the Inflation Reduction Act (IRA) tax credits for purchasing used electric vehicles (EVs), which aimed to address concerns that new EV tax credits

primarily benefit higher-income buyers. We show theoretically that under certain conditions, tax credits for new versus used EVs have the *same* economic incidence because they interact through used EV resale values. However, using confidential dealership transaction data, we find that used EV prices increased by only a limited amount after the IRA was enacted and the tax credits became available, suggesting that the initial economic incidence fell primarily on EV buyers who were eligible for the credit. Bunching of transaction prices below the credit's $25,000 price threshold increased markedly in 2024, when buyers could immediately receive the credit amount as a cash rebate. We then assess the long-run welfare effects of EV tax credits using a novel non-stationary dynamic structural model of new and used vehicle markets.

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Online Appendix

Equitable Energy Transitions? The Efficiency and Distributional Effects of Subsidies for Used Electric Vehicles

Hunt Allcott, Hyuk-soo Kwon, and Tess Snyder

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A Analytical Model Appendix

A.1 Proof of Proposition 1 (Optimal Policy)

As argued in the text, we assume $\mu = 1$ is the optimal policy. Which leads to the following simplification

$$W(\tau_n, \tau_u) = \int_{p_n - \tau_n - V}^{\infty} D_n(x,y)dx + D_n(x,y) \cdot (p_n - c + \phi - \tau_n) + \int_{p_u - \tau_u}^{\infty} D_u(x,y)dy \tag{30}$$

$$+ D_u(x,y) \cdot (\phi - \tau_u) \tag{31}$$

First consider the consumer surplus pieces. Suppose there are prices $(\bar{p_n}, \bar{p_u})$, then by our quasilinearity assumptions, it is a standard application of the envelope theorem that $\frac{dCS}{d\bar{p_x}} = D_x$ for $x \in \{n, u\}$. Let $\bar{p_n} = p_n - \tau_n - p_u$ and $\bar{p_u} = p_u - \tau_u$. Then considering CS over the new and used markets, we have

$$\frac{dCS(\bar{p_n}, \bar{p_u})}{d\tau_n} = \frac{dCS}{d\bar{p_n}}\frac{d\bar{p_n}}{d\tau_n} + \frac{dCS}{d\bar{p_u}}\frac{d\bar{p_u}}{d\tau_n} = D_n \cdot \frac{d(p_n - \tau_n - V)}{d\tau_n} + D_u \cdot \frac{d(p_u - \tau_u)}{d\tau_n}. \tag{32}$$

Utilizing this, we get two first-order conditions by differentiating W with respect to τ_n and τ_u.

$$\frac{dW}{d\tau_n} = -D_n(x,y)\left[\frac{dp_n}{d\tau_n} - 1 - (1-g)\frac{dp_u}{d\tau_n}\right] + D_n(x,y)\left[\frac{dp_n}{d\tau_n} - 1\right] + (p_n - c + \phi - \tau_n) \cdot \frac{dD_n}{d\tau_n} \tag{33}$$

$$- D_u(x,y)\left[\frac{dp_u}{d\tau_n}\right] + \frac{dD_u}{d\tau_n} \cdot (\phi - \tau_u) \tag{34}$$

and

$$\frac{dW}{d\tau_u} = -D_n(x,y)\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D_n(x,y)\frac{dp_n}{d\tau_u} + \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n) \tag{35}$$

$$- D_u(x,y)\left[\frac{dp_u}{d\tau_u} - 1\right] + \frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u) - D_u(x,y). \tag{36}$$

where $x = p_n - \tau_n - V, y = p_u - \tau_u$. To simplify, note that by market clearing $D_n(.)(1-g) = D_u(.)$. Then

$$\frac{dW}{d\tau_n} = \frac{dD_n}{d\tau_n} \cdot (p_n - c + \phi - \tau_n) + \frac{dD_u}{d\tau_n} \cdot (\phi - \tau_u) = 0 \tag{37}$$

$$\frac{dW}{d\tau_u} = \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n) + \frac{dD_u}{d\tau_u} \cdot (\phi - \tau_u) = 0. \tag{38}$$

Solving for τ_n gives

$$\tau_n = p_n - c + \phi + \frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} \cdot (\phi - \tau_u) \tag{39}$$

$$\tau_n = p_n - c + \phi + \frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} \cdot (\phi - \tau_u). \tag{40}$$

Setting these equations equal gives

$$\frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} \cdot (\phi - \tau_u) = \frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} \cdot (\phi - \tau_u) \tag{41}$$

These derivatives are independent of τ_n, τ_u, so either we will have infinitely many solutions (when the ratio of derivatives are the same) or just one. Using the quantity results one can check that these are equal if and only if $g' = 0$. Otherwise, $\tau_u^* = \phi$, which implies $\tau_n^* = p_n - c + \phi$.

A.2 Proof of Proposition 2 (Symmetry)

Omitted from the main text is the regularity condition that $0 \leq x \leq (1-g)\left[p_u(\tau_n) - v_s\right]$. This restriction is because the value of V is lower bounded at v_s.

Proof: Suppose $g' = 0$. Let (p_n, p_u) be the steady-state equilibrium prices under $\{\tau_n, \tau_u\}$. We argue that we can fix p_n and then find a price $\tilde{p}_u$ such that the first and second arguments of demand stay the same. The supply constraints are a function of only p_n and g is fixed, so this would imply the same equilibrium.

For the first argument of demand we require

$$p_n - \tau_n - V(p_u) = p_n - (\tau_n + x) - V(\tilde{p}_u) \tag{42}$$

$$x = V(p_u) - V(\tilde{p}_u) \tag{43}$$

$$x = \left(1 - g\left(\frac{p_u - v_s}{\psi}\right)\right) \cdot (p_u - v_s) - \psi \int_0^{\frac{p_u - v_s}{\psi}} x dP(x) \tag{44}$$

$$- \left[\left(1 - g\left(\frac{\tilde{p}_u - v_s}{\psi}\right)\right) \cdot (\tilde{p}_u - v_s) - \psi \int_0^{\frac{\tilde{p}_u - v_s}{\psi}} x dP(x)\right] \tag{45}$$

but note that $g(.) = P(.)$ so assuming $g' = 0$ between $\frac{p_u - v_s}{\psi}$ and any solution $\frac{\tilde{p}_u - v_s}{\psi}$, we have that

$$x = (1-g) \cdot (p_u - \tilde{p}_u). \tag{46}$$

This is true provided that $\tilde{p}_u \geq v_s$ which is equivalent to

$$\tilde{p}_u = p_u - \frac{x}{(1-g)} \geq v_s \tag{47}$$

implying $x \leq (p_u - v_s)(1-g)$, which is exactly what we assumed.

For the second argument of demand we simply require (using the construction of $\tilde{p}_u$ above)

$$p_u - \tau_u = \tilde{p}_u - (\tau_u - y) \tag{48}$$

$$p_u - \tau_u = p_u - \frac{x}{1-g} - \tau_u + y \tag{49}$$

$$y = \frac{x}{1-g} \tag{50}$$

which is what we wanted to show.

For the reverse direction, assume that $g' < 0$ and suppose for contradiction there exists $x, y > 0$ s.t. $\{\tau_n, \tau_u\}$ and $\{\tau_n + x, \tau_u - y\}$ generate the same steady state outcomes. Let (p_n, p_u) be the steady-state prices under $\{\tau_n, \tau_u\}$. Then to maintain the same new supply we must fix new prices. Then conditioning on the new vehicle stock, we must also fix used prices so scrappage doesn't change.

But now notice that for any $x, y > 0$,

$$D_n(p_n - (\tau_n + x) - V(p_u), p_u - (\tau_u - y)) > D_n(p_n - \tau_n - V(p_u), p_u - \tau_u). \tag{51}$$

This is simple to see by the signs of D_n^1 and D_n^2 since new vehicles are cheaper and used vehicles are more expensive on the left-hand side. Therefore, there exists no such $x, y > 0$ such that the market is in equilibrium for prices p_n, p_u.

A.3 Proof of Proposition 3

The restricted-market clearing conditions are

$$D_n(p_n - \mu\tau_n - V(p_u), p_u - \mu\tau_u) = S(p_n) \tag{52}$$

$$D_u(p_n - \mu\tau_n - V(p_u), p_u - \mu\tau_u) = (1-g) \cdot S(p_n) \tag{53}$$

A.3.1 Incidence of new subsidies

We totally differentiate the market clearing conditions

$$D_n^1 \left(\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n} \right) = S' \frac{dp_n}{d\tau_n} \tag{54}$$

$$D_u^2 \cdot \frac{dp_u}{d\tau_n} = (1-g) S' \frac{dp_n}{d\tau_n}. \tag{55}$$

Rearranging yields

$$\frac{dp_n}{d\tau_n} = \frac{\mu D_n^1 + (1-g) D_n^1 \frac{dp_u}{d\tau_n}}{D_n^1 - S'} \tag{56}$$

$$\frac{dp_n}{d\tau_n} = \frac{D_u^2 \frac{dp_u}{d\tau_n}}{(1-g)S'}. \tag{57}$$

Solving this system gives the new subsidy incidence rates given in Proposition 3.

A.3.2 Incidence of used subsidies

We totally differentiate the market clearing conditions

$$D_n^1 \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u} \right) = S' \frac{dp_n}{d\tau_u} \tag{58}$$

$$D_u^2 \left(\frac{dp_u}{d\tau_u} - \mu \right) = (1-g) \cdot S' \frac{dp_n}{d\tau_u}. \tag{59}$$

Rearranging yields

$$\frac{dp_n}{d\tau_u} = \frac{(1-g) D_n^1 \frac{dp_u}{d\tau_u}}{D_n^1 - S'} \tag{60}$$

$$\frac{dp_n}{d\tau_u} = \frac{D_u^2 \frac{dp_u}{d\tau_u} - \mu D_u^2}{(1-g)S'} \tag{61}$$

Solving this system gives the used subsidy incidence rates given in Proposition 3.

A.3.3 Quantity effects

By market clearing in steady-state and the incidence results above, we get

$$\frac{dD_n}{d\tau_n} = \frac{dS(p_n)}{d\tau_n} = S' \frac{dp_n}{d\tau_n} \tag{62}$$

$$\frac{dD_n}{d\tau_u} = \frac{dS(p_n)}{d\tau_u} = S' \frac{dp_n}{d\tau_u} = S'(1-g)\frac{dp_n}{d\tau_n} \tag{63}$$

$$\frac{dD_u}{d\tau_n} = (1-g)\frac{dS(p_n)}{d\tau_n} = (1-g)\frac{dD_n}{d\tau_n} \tag{64}$$

$$\frac{dD_u}{d\tau_n} = (1-g)\frac{dS(p_n)}{d\tau_u} = (1-g)\frac{dD_n}{d\tau_u} \tag{65}$$

A.4 Proof of Proposition 4

The long-run steady-state market clearing conditions are as follows:

$$D_n(p_n - \mu\tau_n - V(p_u),\ p_u - \mu\tau_u) = S(p_n) \tag{66}$$

$$D_u(p_n - \mu\tau_n - V(p_u),\ p_u - \mu\tau_u) = (1 - g(p_u))\, S(p_n). \tag{67}$$

A.4.1 Incidence of New Vehicle Subsidy

We totally differentiate the market clearing conditions giving

$$D_n^1 \cdot \left(\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right) + D_n^2 \frac{dp_u}{d\tau_n} = S' \frac{dp_n}{d\tau_n} \tag{68}$$

$$D_u^1 \cdot \left(\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right) + D_u^2 \frac{dp_u}{d\tau_n} = S' \frac{dp_n}{d\tau_n}(1-g) - Sg' \frac{dp_u}{d\tau_n}. \tag{69}$$

Rearranging gives

$$\frac{dp_n}{d\tau_n} = \frac{\mu D_n^1 + \frac{dp_u}{d\tau_n}\left[(1-g)D_n^1 - D_n^2\right]}{D_n^1 - S'} \tag{70}$$

$$\frac{dp_n}{d\tau_n} = \frac{\mu D_u^1 + \frac{dp_u}{d\tau_n}\left[(1-g)D_u^1 - D_u^2 - g'S\right]}{D_u^1 - S'(1-g)}. \tag{71}$$

Solving this system gives the left side of Proposition 4. Explicitly,

$$\Lambda = (D_n^1 D_u^2 - D_n^2 D_u^1) - g'SS' + g'SD_n^1 + S'\left[D_u^1 - D_u^2\right] + S'(1-g)\left[D_n^2 - D_n^1\right] > 0 \tag{72}$$

A.4.2 Incidence of Used Vehicle Subsidy

We totally differentiate the market clearing conditions giving

$$D_n^1 \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) + D_n^2 \left(\frac{dp_u}{d\tau_u} - \mu\right) = S' \frac{dp_n}{d\tau_u} \tag{73}$$

$$D_u^1 \left(\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right) + D_u^2 \left(\frac{dp_u}{d\tau_u} - \mu\right) = (1-g)S' \frac{dp_n}{d\tau_u} - g' \frac{dp_u}{d\tau_u} S. \tag{74}$$

By rearranging we get

$$\frac{dp_n}{d\tau_u} = \frac{\mu D_n^2 + \frac{dp_u}{d\tau_u}\left[D_n^1(1-g) - D_n^2\right]}{D_n^1 - S'} \tag{75}$$

$$\frac{dp_n}{d\tau_u} = \frac{\mu D_n^2 + \frac{dp_u}{d\tau_u}\left[D_u^1(1-g) - D_u^2 - g'S\right]}{D_u^1 - (1-g)S'} \tag{76}$$

Solving this system gives the right side of Proposition 4.

A.5 Proof of Proposition 5

First, consider the market clearing condition that $D_n(.) = S(p_n)$, therefore we must also have that

$$\frac{dD_n}{d\tau_n} = \frac{dS(p_n)}{d\tau_n} = S'\frac{\mu\left[D_n^1 D_u^2 - D_u^1 D_n^2) + D_n^1 g'S\right]}{\Lambda} \geq 0 \tag{77}$$

$$\frac{dD_n}{d\tau_u} = \frac{dS(p_n)}{d\tau_u} = S'\frac{\mu\left[(1-g)(D_n^1 D_u^2 - D_n^2 D_u^1) + g'SD_n^2\right]}{\Lambda} \tag{78}$$

For the quantity effects of used demand we solve directly using the general steady-state incidence results from Proposition 4.

$$\frac{dD_u}{d\tau_n} = D_u^1\left[\frac{dp_n}{d\tau_n} - \mu - (1-g)\frac{dp_u}{d\tau_n}\right] + D_u^2\frac{dp_u}{d\tau_n} \tag{79}$$

$$= D_u^1 \cdot \frac{\mu\left[D_n^1 D_u^2 - D_u^1 D_n^2) + D_n^1 g'S\right] - \mu\Lambda - (1-g)\mu\left[D_n^1 S'(1-g) - D_u^1 S'\right]}{\Lambda} \tag{80}$$

$$+ D_u^2 \cdot \frac{\mu\left[D_n^1 S'(1-g) - D_u^1 S'\right]}{\Lambda} \tag{81}$$

$$= \frac{\mu D_u^1 g'S'S - \mu S'(1-g)\left[D_n^1 D_u^2 - D_u^1 D_n^2\right]}{\Lambda} \tag{82}$$

Next we repeat the same procedure for used subsidies

$$\frac{dD_u}{d\tau_u} = D_u^1\left[\frac{dp_n}{d\tau_u} - (1-g)\frac{dp_u}{d\tau_u}\right] + D_u^2\left[\frac{dp_u}{d\tau_u} - \mu\right] \tag{83}$$

$$= D_u^1 \cdot \frac{\mu\left[(1-g)(D_n^1 D_u^2 - D_n^2 D_u^1) + g'SD_n^2\right] - (1-g)\mu\left[(D_n^1 D_u^2 - D_n^2 D_u^1) - D_u^2 S' + D_n^2(1-g)S'\right]}{\Lambda} \tag{84}$$

$$+ D_u^2 \cdot \frac{\mu\left[(D_n^1 D_u^2 - D_n^2 D_u^1) - D_u^2 S' + D_n^2(1-g)S'\right] - \mu\Lambda}{\Lambda} \tag{85}$$

$$= \frac{\mu D_u^2 g'S'S + \mu g'S\left[D_u^1 D_n^2 - D_n^1 D_u^2\right] + \mu S'(1-g)^2\left[D_n^1 D_u^2 - D_u^1 D_n^2\right]}{\Lambda} \geq 0 \tag{86}$$

A.6 Proof of Proposition 6

Using the results from Proposition 5, it is simple algebra to show that

$$\frac{dD_n}{d\tau_n} - \frac{dD_n}{d\tau_u} = S' \frac{\mu \left[D_n^1 D_u^2 - D_u^1 D_n^2) + D_n^1 g' S \right]}{\Lambda} - S' \frac{\mu \left[(1-g)(D_n^1 D_u^2 - D_n^2 D_u^1) + g' S D_n^2 \right]}{\Lambda} \tag{87}$$

$$= \frac{S'\mu}{\Lambda} \cdot \left(g \left[D_n^1 D_u^2 - D_u^1 D_n^2 \right] - g' S D_n^2 \right) \geq 0 \tag{88}$$

This implies that the increase in D_n under new subsidies is unambiguously larger than the change under used subsidies.

We now consider changes in used demand

$$\frac{dD_u}{d\tau_n} - \frac{dD_u}{d\tau_u} = \frac{\mu D_u^1 g' S' S - \mu S'(1-g) \left[D_n^1 D_u^2 - D_u^1 D_n^2 \right]}{\Lambda} \tag{89}$$

$$- \frac{\mu D_u^2 g' S' S + \mu g' S \left[D_u^1 D_n^2 - D_n^1 D_u^2 \right] + \mu (1-g) S' (1-g) \left[D_n^1 D_u^2 - D_u^1 D_n^2 \right]}{\Lambda} \tag{90}$$

$$= \frac{\mu g' S' S \left[D_u^1 - D_u^2 \right] + \mu g' S \left[D_n^1 D_u^2 - D_u^1 D_n^2 \right] + \mu S'(1-g) g \left[D_n^1 D_u^2 - D_u^1 D_n^2 \right]}{\Lambda} \tag{91}$$

This is ambiguous with the first two terms being negative while the last is positive.

A.7 Proof of Proposition 7

The short-run market clearing conditions are

$$D_n(p_{nt} - \mu\tau_n - \tilde{V}(\tilde{p}_{u,t+1}), p_{ut} - \mu\tau_u) = S(p_{nt}) \tag{92}$$

$$D_u(p_{nt} - \mu\tau_n - \tilde{V}(\tilde{p}_{u,t+1}), p_{ut} - \mu\tau_u) = S_{t-1} \cdot (1 - g(p_{ut})) \tag{93}$$

where the change in the price expectation $\tilde{p}_{u,t+1}$ is exogenous to our model. We totally differentiate

$$D_n^1 \cdot \left[\frac{dp_{nt}}{d\tau_u} - (1-g) \frac{d\tilde{p}_{u,t+1}}{d\tau_u} \right] + D_n^2 \left[\frac{dp_{ut}}{d\tau_u} - \mu \right] = S' \frac{dp_{nt}}{d\tau_u} \tag{94}$$

$$D_u^1 \cdot \left[\frac{dp_{nt}}{d\tau_u} - (1-g) \frac{d\tilde{p}_{u,t+1}}{d\tau_u} \right] + D_u^2 \left[\frac{dp_{ut}}{d\tau_u} - \mu \right] = -S_{t-1} g' \frac{dp_{ut}}{d\tau_u}. \tag{95}$$

Rearranging yields

$$\frac{dp_{nt}}{d\tau_u} = \frac{\mu D_n^2 - \frac{dp_{ut}}{d\tau_u} D_n^2 + (1-g) D_n^1 \frac{d\tilde{p_{u,t+1}}}{d\tau_u}}{D_n^1 - S'} \tag{96}$$

$$\frac{dp_{nt}}{d\tau_u} = \frac{\mu D_u^2 + \frac{dp_{ut}}{d\tau_u} \left[-D_u^2 - S_{t-1} g'\right] + (1-g) D_u^1 \frac{d\tilde{p_{u,t+1}}}{d\tau_u}}{D_u^1} \tag{97}$$

Solving this system gives the results in Proposition 7.

B Bunching Model Appendix

To motivate our empirical estimation of the value of the subsidy from the observed bunching, we derive the relationship between the observed price distribution under the subsidy policy and the counterfactual price distribution. We show that, under certain assumptions over the behavior of price shifts, the excess bunching at $25,000 can be used to quantify the pass-through of the subsidy.

B.1 Setup

Let $P_1(x)$ be the distribution of prices under the potential outcome where subsidies are offered. Let $P_0(x)$ be the distribution of prices in the counterfactual scenario without subsidies. Suppose that x represents prices in thousands of dollars and the maximum price cap on eligible transactions is at $x = 25$. Assume that $P_0(x)$ is continuous everywhere and $P_1(x)$ is continuous except at possibly $x = 25$ (and is right-continuous at $x = 25$ based on the characteristics of cumulative distribution functions).

B.2 Case 1: No downward bunching

For the baseline case, we make three assumptions. First, we assume that any transaction priced strictly above 25 in the absence of subsidies would remain strictly above 25. Second, we assume that no transaction priced weakly below 25 in the counterfactual scenario would jump to strictly above 25 under subsidies. Third, fix $\Delta \geq 0$, we assume that every transaction strictly below 25 under P_0 would increase by the minimum of Δ and the distance to 25. Conditions one and two jointly imply that $P_1(25) = P_0(25)$. Adding in assumption three yields

$$P_1(x) = \begin{cases} P_0(x) & \text{if } x \geq 25 \\ P_0(x - \Delta) & \text{if } x < 25. \end{cases} \tag{98}$$

Now suppose that we have the distributions P_1 and P_0 and we want to solve for the value of the subsidy Δ that explains these two distributions given our three assumptions. We can express Δ by our assumptions

as

$$\Delta = 25 - \sup\{x | P_0(x) < \lim_{x \to 25^-} P_1(x)\}. \tag{99}$$

Since we have $P_1(25) = P_0(25)$, it follows that

$$P_0(25) - P_0(25 - \Delta) = P_1(25) - \lim_{x \to 25^-} P_1(x). \tag{100}$$

Now suppose that we create piecewise linear functions $\bar{P}_0$ and $\bar{P}_1$ approximating P_0 and P_1, respectively, with breaks at every thousand dollar increment and matching the values at the endpoints. This is consistent with estimating the distribution via a histogram of the density graph with bins of width 1. Then we trivially have

$$\bar{P}_1(25) - \bar{P}_1(24) = P_1(25) - \lim_{x \to 25^-} P_1(x) + \left(\lim_{x \to 25^-} P_1(x) - P_1(24) \right). \tag{101}$$

Using equation (101) to re-express equation (100),

$$P_0(25) - P_0(25 - \Delta) = \bar{P}_1(25) - \bar{P}_1(24) - \left(\lim_{x \to 25^-} P_1(x) - P_1(24) \right) \tag{102}$$

$$P_0(25) - P_0(25 - \Delta) = \bar{P}_1(25) - \bar{P}_1(24) - (P_0(25 - \Delta) - P_0(24 - \Delta)) \tag{103}$$

$$\bar{P}_0(25) - \bar{P}_0(25 - \Delta) = \bar{P}_1(25) - \bar{P}_1(24) - \left(\bar{P}_0(25 - \Delta) - P_0(24 - \Delta)\right) \tag{104}$$

where equation (103) follows by assuming that P_0 is smooth and will hold for the true value of Δ, and equation (104) holds by assumptions on $\bar{P}_0$ and utilizing an identity. Restructuring a last time yields

$$\bar{P}_0(24) - P_0(24 - \Delta) = \left(\bar{P}_1(25) - \bar{P}_1(24)\right) - \left(\bar{P}_0(25) - \bar{P}_0(24)\right) \tag{105}$$

To yield a final dollar value for our empirical estimate, we make the assumption that $\bar{P}_0(24 - \Delta) = P_0(24 - \Delta)$. Then, in words, the value of the subsidy is the cutoff Δ such that the excess mass in the last bin adjacent to 25 in the estimated distribution equals the mass from $[24 - \Delta, 24]$ of the counterfactual distribution.

B.3 Case 2: Adding downward bunching

Now consider the scenario where assumptions two (prices under 25 remain weakly below) and assumptions three (all prices under 25 increase by Δ or are at the price cap) remain, but we relax the first assumption and allow some prices over 25 to decrease. Concretely, we modify assumption one to be that any transaction priced above 25 in the counterfactual would remain weakly above 25 under subsidies.

Our objective is not to calculate the value of downward bunching, only to account for its presence in our calculation of the value associated with the upwards bunching. By our updated assumption one, suppose that a transaction in P_1 is priced weakly less than 25, then either a) under P_0 it is weakly less than 25 or b) the transaction is exactly 25 under P_1 and the price is greater than 25 under P_0. Therefore, if we set $\bar{P}_1(25) = P_0(25)$ we remove observations from case (b). This new distribution includes only transactions that were weakly below 25 under P_0, and the above analysis from case 1 holds verbatim.

To operationalize this, suppose that no transaction bunches downwards if it is more that $\$X$ above 25, then $P_0(25+X) = P_1(25+X)$, so

$$P_1(25) - P_0(25) = P_0(25+X) - P_1(25+X) + P_1(25) - P_0(25) \tag{106}$$
$$= [P_0(25+X) - P_0(25)] - [P_1(25+X) - P_1(25)] \tag{107}$$

So combined we have

$$\bar{P}_1(25) = P_0(25) = P_1(25) + [P_1(25+X) - P_1(25)] - [P_0(25+X) - P_0(25)] \tag{108}$$

which can be plugged into equation (105) for an updated value of bunching accounting for downward bunching.

C Data Appendix

C.1 Tax Liability

In this section we describe our results and methodology for computing the average tax liability of used EV buyers. As noted in Section 2, the tax credit for eligible used EV purchases was non-refundable before January 1, 2024, when the dealership transfer option was implemented. Therefore, it is of interest to calculate the average tax liability of buyers who purchase used EVs costing under $25,000.

One basis of our analysis is the second choice data we obtain for new vehicle purchases. Thus, we make the assumption that new vehicle buyers and used vehicle buyers purchasing a similarly priced vehicle will have the same tax liability. We then utilize the Cox transaction data, which includes price, to calculate the average selling price of a given new vehicle make and model between August 2022 and December 2023. We keep models with average selling price below $26,000 (to maintain a decent sample) which provides 15 vehicles. Of note is that all of these are GVs, therefore, our analysis also requires the assumption that a purchaser's tax liability is independent of vehicle powertrain. We filter the second choice data for only these models and keep the income variable.

Table A1: **Tax Liability Statistics**

		Share with tax liability			Value of $4k tax subsidy | tax liability > 0			
Income	(1) Share of purchases < $26k	(2) Married	(3) Single	(4) Head of household	(5) Married	(6) Single	(7) Head of household	(8) Average value of $4k tax subsidy
$1-20,000	6.0%	0.0%	16.0%	0.0%	$4,000	$338	$0	$42
$20,000-25,000	4.4%	0.4%	77.5%	2.9%	$603	$905	$258	$457
$25,000-30,000	5.8%	22.6%	85.9%	6.6%	$498	$1,405	$433	$778
$30,000-40,000	12.5%	46.6%	93.3%	14.4%	$711	$2,208	$933	$1,337
$40,000-50,000	10.1%	56.4%	96.7%	50.8%	$1,512	$3,340	$1,434	$2,259
$50,000-75,000	24.3%	77.2%	98.1%	79.4%	$3,029	$4,000	$2,891	$3,178
$75,000-100,000	13.1%	91.8%	99.0%	95.3%	$4,000	$4,000	$4,000	$3,793
$100,000-200,000	19.3%	98.2%	99.4%	98.5%	$4,000	$4,000	$4,000	$3,939
$200,000-500,000	4.0%	99.8%	99.7%	99.3%	$4,000	$4,000	$4,000	$3,991
$500,000-1,000,000	0.3%	99.9%	99.7%	99.6%	$4,000	$4,000	$4,000	$3,996
$1,000,000+	0.3%	99.9%	99.8%	99.6%	$4,000	$4,000	$4,000	$3,997
Total	1.0%	67.1%	91.3%	62.8%	$2,751	$3,205	$2,479	$2,675
Value of $4k tax subsidy under IRA eligibility					$1,823	$2,603	$1,586	$2,004

Notes: Single in columns (3) and (6) include both single filers and married filing separately. Column (1) is the share of purchases by income group, utilizing the second choice data, among new vehicle models identified as costing under $26,000 using Cox Automotive data. Columns 2-4 identifies the share of filers having any tax liability greater than zero. Conditioning on this, columns 5-7 show the minimum of $4k and the average tax liability within the income by filing status group. Column 8 is a weighted average of all filers. The last line utilizes the $75k, $112.5k, and $150k limits in the IRA for eligibility by single, head of household, and married filing jointly status, respectively, and accounts for zero liability filers.

We compute tax liability utilizing IRS statistics of income (SOI) for tax year 2021 (IRS 2024a). For each adjusted gross income (AGI) bin by filing status, we observe the total number of tax returns, total tax liability, and the number of returns with tax liability greater than zero. For the purposes of EV subsidies under the IRA, single filers and married filing separately filers have the same income threshold, so we merge them into a category called "single". We calculate at the level of income by filing status the share of filers with nonzero tax liability and the value of a $4,000 tax subsidy conditional on having strictly positive tax liability. These results are in Table A1, columns 2-4 and 5-7, respectively.

We merge the IRS data to the filtered second choice data by assuming that the reported income of purchasers is the same as their AGI. Column 2 of Table A1 denotes what share of total purchases within this subsample costing under $26,000 occurs within each income bin. Column 8 is the weighted average of the value of $4k subsidy for all filers in a given income bin. The last row of the table utilizes the $75k,

$112.5k, and $150k income eligibility limits under the IRA for single, head of household, and married filing jointly filers, respectively. Conditioning on these income limits, we take the weighted average (weights are the share of purchases) of the value of a $4k subsidy among all filers of a given type, accounting for those with zero tax liability. The last row of column 8 is just a simple average.

C.2 Externality Calculation

A key dimension of the welfare analysis for the various EV policies will be their effect on externalities, as consumers substitute across vehicle ages and powertrains. We compute yearly vehicle externalities along four dimensions: manufacturing CO2 emissions, CO2 and local air pollution due to driving, weight externalities due to accidents, and fiscal externalities from utility markups on electricity or fuel taxes. We assume a social cost of carbon of $241 (in July 2023 dollars), following US EPA (2023).

The pollution due to driving and fiscal externalities will depend on miles travelled. On average, older vehicles are driven for fewer miles, but this is likely due to an individual-specific parameter, rather than a vehicle parameter. In the simulation we will likely have consumers substituting older vehicles for newer vehicles. We will make the assumption that in this scenario the owner will not change the number of miles that they would travel. Therefore, we fix yearly mileage at 10,529, the average among all registered vehicles in 2022 taken from NHTSA (2022).

Manufacturing CO2 emissions We use values directly from Kelly et al. (2022), which is broken down by powertrain {EV, GV, PHEV} where we assume that the externality for hybrids is the average of PHEV and GV. The larger externalities of battery production makes the manufacturing externality of EVs and PHEVs larger than GVs and hybrids.

CO2 and local air pollution emissions from driving For local air pollutants we use the marginal damage estimates from Holland et al. (2016). For EVs we use the regional short-run marginal emission rates from Holland et al. (2016), which we aggregate across zip codes by total vehicle miles traveled following Holland et al. (2016), and then create a national statistic weighting by 2023 state new EV sales share. The state weighting is important because states with higher EV sales have cleaner electricity production, implying a simple average would overstate the local pollution. We utilize EV fuel efficiency to compute local damages per mile for each model.

For GVs, we compute the damages from tailpipe emissions. For each model we construct CO2 emissions using fuel efficiency statistics. We take local pollutant emissions per gallon from US EPA (2024), and then apply the same weighting as above. We assume that 63 percent of PHEV miles are on gasoline and 37 percent are on electricity, following Plötz et al. (2020).

Accident Externalities We follow Anderson and Auffhammer (2014) in calculating the increase in crash fatalities due to driving a vehicle compared to the lightest in our dataset. This is the product of the accident probability and incremental death probability based on the weight of the vehicle, both of which we take from Anderson and Auffhammer (2014). We utilize a $13.2 million value of statistical life (VSL) from US Department of Transportation (2024), which multiplied by the increase in expected number of crash fatalities gives the accident externality from driving a heavier vehicle. The accident probability is constant across vehicles, so 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 then depends on its fuel usage per mile (either electricity or gas), miles traveled as described above, and the weighted markup or tax.

D Reduced-Form Evidence Appendix

D.1 Context of Price Triple Difference Plot

To provide context for the triple difference results in Figure 2, we show the raw price trends around January 2023 and January 2024 for each of the four EV by predicted price groups in Figure A1. The main changes over the 2023 analysis period occur in the expensive EV and GV groups, where transaction prices in the expensive EV group trend downward significantly in comparison to the expensive GVS. The prices of cheaper vehicles display are relatively stable in 2023, but we see a slight downward trend for cheaper EVs throughout 2024.

D.2 Price Prediction Regression

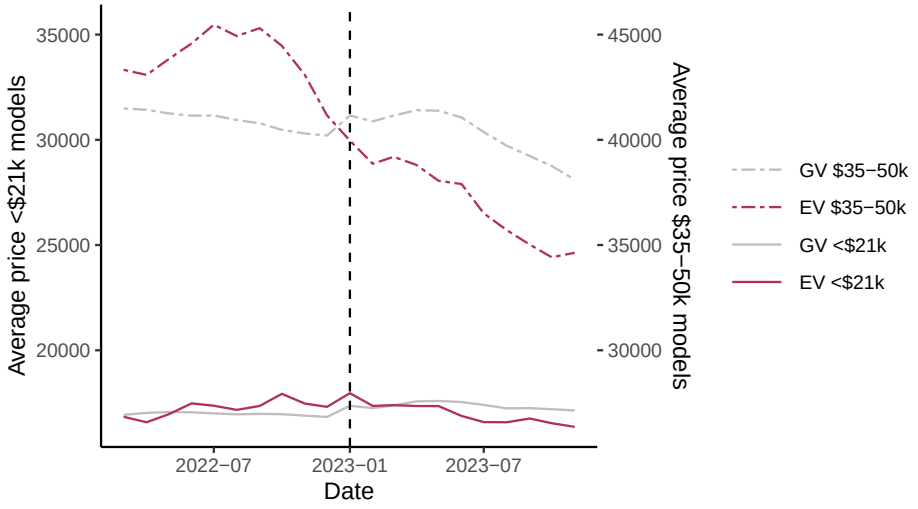
This section shows the estimation results from the price prediction regression described in Section 5.1.1. Table A2 shows the coefficient on odometer and the fixed effects, along with observation count.

D.3 Tests of Anticipation Effects Around Policy Changes

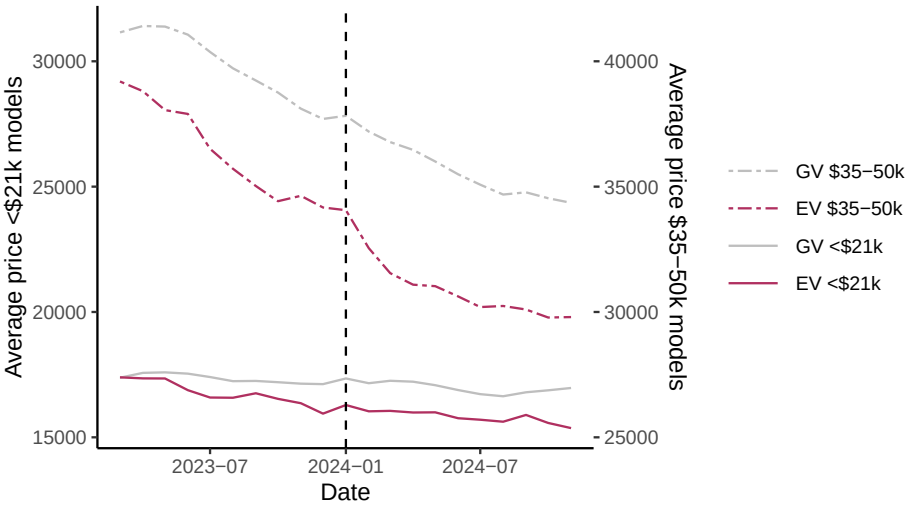
The goal of this section is to assess potential effects of the tax credit on the used vehicle market through channels other than transaction prices. For example, it could be that dealerships change financing terms rather than the upfront price of a vehicle in response to the policy. Because the used EV tax credit has an

Figure A1: **Raw Price Trends by Treatment Group**

(a) 2023



(b) 2024



eligibility requirement based on income, we may expect to see the composition of buyers change around the start date of the policy. If enough of the market is eligible for the credit and wait to purchase until after the policy, the total quantity of transactions could shift around the start date. The share of transactions that occur between individuals versus through dealerships may also shift based on the fact that eligible transactions must occur through licensed dealerships.

These characteristics of the used vehicle market are important in interpreting the results of the price

Table A2: **Price Prediction Regression**

	(1) ln(Transaction Price)	
ln(Odometer)	-0.1067	(0.0002)
Fixed effects		
MY	Yes	
MY x Months Post 7/21	Yes	
MY x Model	Yes	
Month-Year	Yes	
Dealership	Yes	
Observations	4,133,028	

event studies in Section 5. In order to understand the price response to the tax credit, we need to compare the same type of transactions before and after the policy changes. If the financing terms or type of consumer differ before and after the event, the comparison is invalid. Based on the evidence discussed below, we do not observe a significant change in these characteristics over our period of analysis, which alleviates these concerns.

D.3.1 Financing Terms

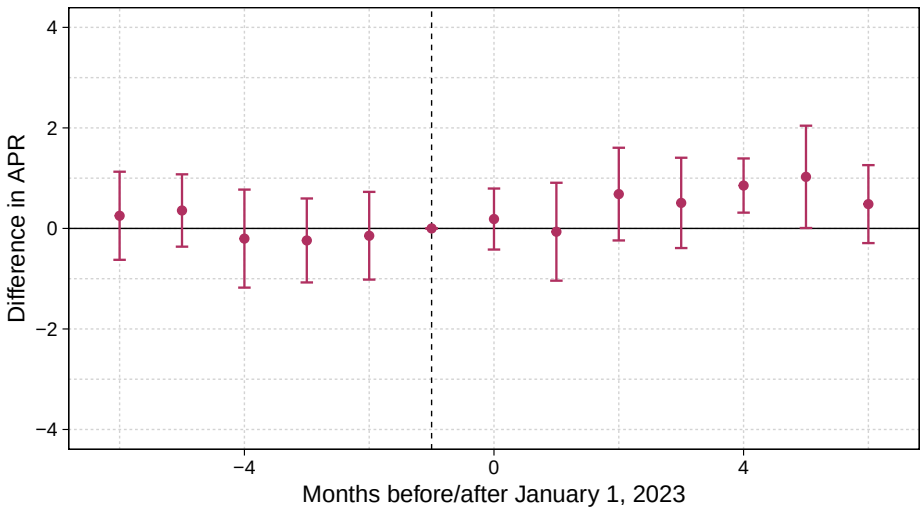
In this section, we present results for the annual percentage rate (APR) of the loans. Figure A2 shows the results of our triple-difference specification from Section 5.1.1 with APR as the outcome variable and standard errors clustered at the model level. We do see a statistically significant positive effect in period 4 but not prior to that in the first months of the policy implementation. Given the effect from the corresponding triple-differences estimation shown in Table A3, we reject APR increases of more than 0.955 percent with 95 percent confidence. As comparison, the mean APR in the treatment group of cheap EVs is 10.40 percent.

While we do see some evidence of an increase in APR, this effect is relatively small and does not occur immediately. This still shows that the effective price of vehicle transactions do not have an immediate, significant response to the policy change.

D.3.2 Buyer Income

It is possible that buyers of eligible vehicles would sort by income around the policy event. Higher-income ineligible buyers may choose to buy before the tax credit implementation if they expect prices to increase afterwards. Lower-income eligible buyers may choose to wait to purchase their vehicle until after January

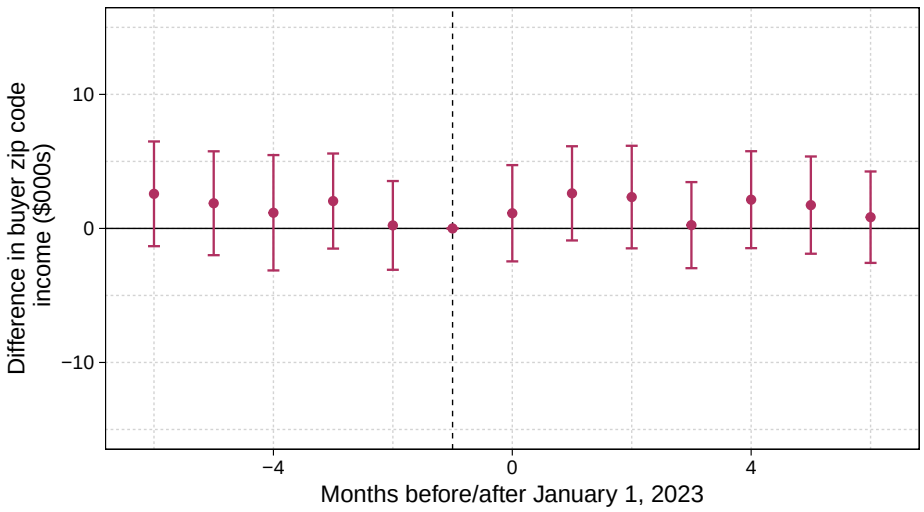
Figure A2: **APR Triple-Differences Event Study**



1, 2023 so that they can claim the tax credit on their purchase. If either or both of these are happening, we would expect to see the average buyer income decrease after January 2023.

We do not observe the income of each buyer, but we do observe their zip code. We use the median household income in the zip code as a proxy for buyer income. Figure A3 shows the results from our triple-difference specification from Section 5.1.1 with median household income in the buyer zip code as the outcome variable and standard errors clustered at the model level. We do not see evidence of sorting by income around the policy event based on this event study. Given the effect from the corresponding triple-differences estimation shown in Table A3, we reject a difference in average buyer income from before versus after the policy of more than $955 with 95 percent confidence. This lends further evidence that the pre and post-periods consist of comparable transactions.

Figure A3: **Buyer zip code income triple-differences event study**



D.3.3 Quantity Effect

To further understand if buyers select transaction times around the policy implementation, we look at the trends in transaction quantity around January 2023. If potential buyers in the pre-period are instead waiting to purchase until after the tax credit is introduced, we would expect to see a reduction in transactions for eligible EVs right before the policy and a spike right at implementation.

Because the Cox transactions do not represent the entire US market, we use the Experian data to capture representative used vehicle transaction quantities. The Experian data has monthly sales volumes for each vehicle type defined as a model by MY. The sample consist of used vehicle transactions sold to individuals. In order to construct the treatment and control groups, we additionally need to know information about prices. We construct the control group based on price as the set of vehicle types with greater than 50 percent of transactions below $21,000 in 2023 Q1 in the Cox data. Similarly, we take the control group as the set of vehicle types with greater than 50 percent of transactions between $35,000 and $50,000.

There is very little difference in the resulting treatment group between using this method and assigning treatment status based on mean price, but this method performs much better for constructing the control group. The sample of vehicle types with mean price between $35,000 and $50,000 includes vehicle types with less than 30 percent of transactions in that price range and up to 8 percent of transactions below $21,000. The current control group includes vehicle types that primarily have 0 percent of transactions below $21,000 and at most about 3 percent below $21,000.

Additionally, we limit the sample to vehicle types with MYs before 2022 to reduce the trends driven by the introduction of newer models into the used vehicle market. This trend still exists to some extent, and the

quantities in the control group are increasing over time because of this. The newer models are more likely to be in the more expensive category.

We use the following triple-difference event study specification weighting observations by the 2022 monthly average number of transactions:

$$q_{jyt} = \sum_{k=T_{\text{pre}}}^{T_{\text{post}}} \gamma_k^3 G_{jy} EV_j \mathbb{1}\{k+t=\tilde{T}\} + \sum_{k=T_{\text{pre}}}^{T_{\text{post}}} \gamma_k^1 G_{jy} \mathbb{1}\{k+t=\tilde{T}\} + \sum_{k=T_{\text{pre}}}^{T_{\text{post}}} \gamma_k^2 EV_j \mathbb{1}\{k+t=\tilde{T}\} + (EV_j \times G_{jy}) + EV_j + G_{jy} + (\lambda^{make_j} \times \lambda^t) + \lambda^j + \lambda^y + \epsilon_{jyt} \quad (109)$$

where q_{jyt} monthly transaction quantity for vehicle model j and MY y divided by the average monthly transactions from 2022 and G_{jy} represents the price group as described above. We scale and weight transaction quantities by the 2022 monthly average in order to capture the representative change in quantity above a baseline level without using an outcome variable in logs. We cannot use a log specification because many vehicle types in our sample have a transaction quantity of 0 in multiple months during this period. Cheaper GVs have much higher transaction levels than any other category, so changes in transaction quantities in this category dominate the results based on unscaled levels. The scaled transaction quantity tells us how much the transaction quantity changes compared to a pre-policy baseline level in a way that is comparable across models.

Figure A4 shows the results of the triple-difference event study specification with standard errors clustered at the vehicle type level. We do not see evidence that the transaction quantity for cheap EVs is responding to the policy event.

Figure A5 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 GV. As discussed above, 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 increasing quantities of newer vehicles being introduced into the used market. The quantity of cheap EVs is decreasing up until the start of 2023, after which we see a modest jump back up. However, we see a similar trend for the cheap GVs.

Figure A6 shows the average scaled transaction quantity for each group. While the average scaled transaction quantity for cheap EVs is lower in December 2022 than in January 2023, it is following a pre-existing trend for this group. As we see in the raw totals above, this decrease is occurring for cheap GVs as well.

Figure A4: **Quantity Triple-Differences Event Study**

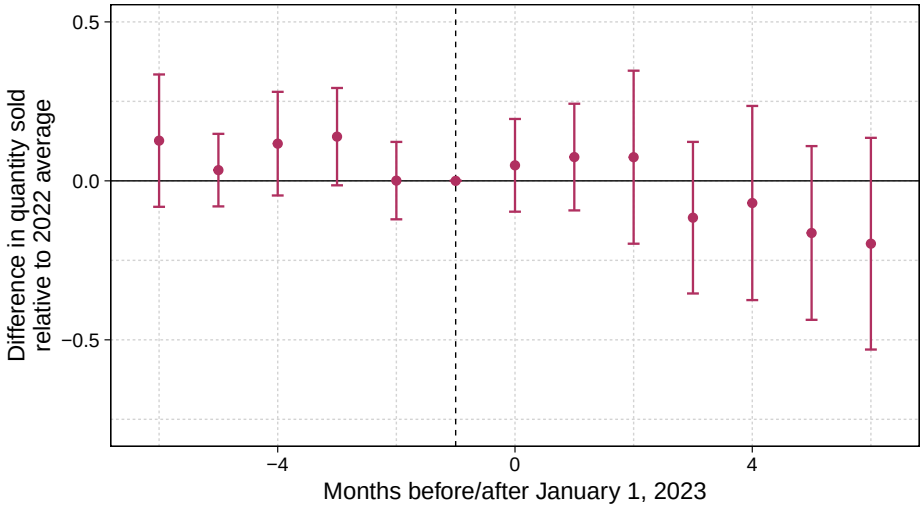
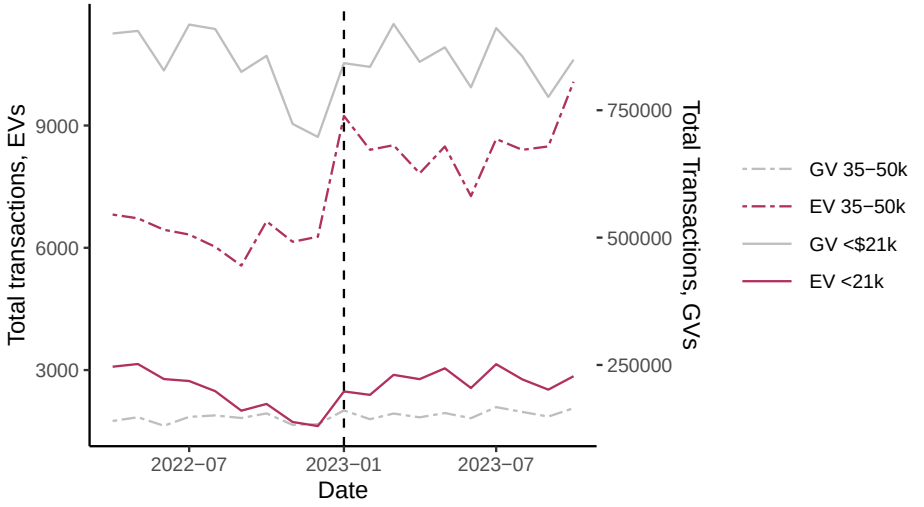


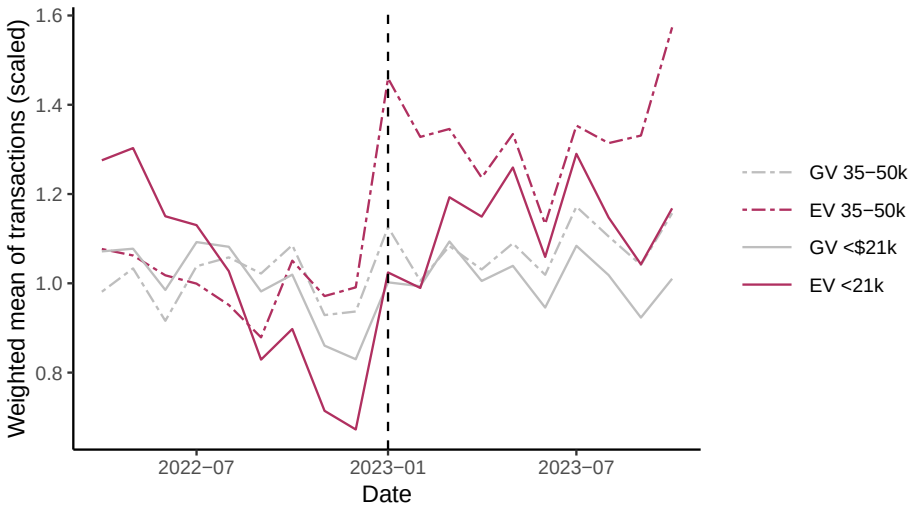
Figure A5: **Raw Transaction Quantity by Treatment Group**



D.3.4 Changes in Dealership Transaction Shares

It is possible that the share of eligible used EV transactions occurring through dealerships would increase due to the policy implementation. The tax credit can only be claimed for transactions through eligible dealers. This share could increase if there were additional transactions due to the tax credit and these additional transactions occurred through dealerships. Additionally, we could see this share increase if individuals

Figure A6: **Average Scaled Transaction Quantity by Treatment Group**



who would have sold their used EV in a person-to-person transaction decide to sell their vehicle through a dealership. Because we do not see a quantity effect in Section D.3.3, we focus on this second explanation.

We apply the empirical strategy from Section D.3.3 with dealership share of transactions as the outcome variable. Figure A7 shows the results of this triple-difference event study specification around the 2023 policy event. Figure A8 shows the corresponding trends in the raw data. We do not see evidence that the dealership share of transactions responded to the policy event. Because we see no effect on quantity, this additionally suggests that individuals did not immediately shift their selling behavior due to the policy. This makes sense if sellers are not attentive to the policy or do not expect to receive additional payment from dealerships for potentially eligible vehicles.

We additionally apply this analysis to the January 2024 policy event, which specifically impacts the role of dealerships. It would be reasonable to expect that dealerships could capture more of the value of the tax credit after consumers have the option to immediately claim it through the dealership. If this is true and the added benefit flows through to used vehicle sellers, we would expect to see the dealership share increase. However, based on the results of the triple-differences event study shown in Figure A9, we do not see an effect immediately after the new dealership rules come into effect. Our analysis here includes fewer post-periods based on the end date of our sample of the Experian data.

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

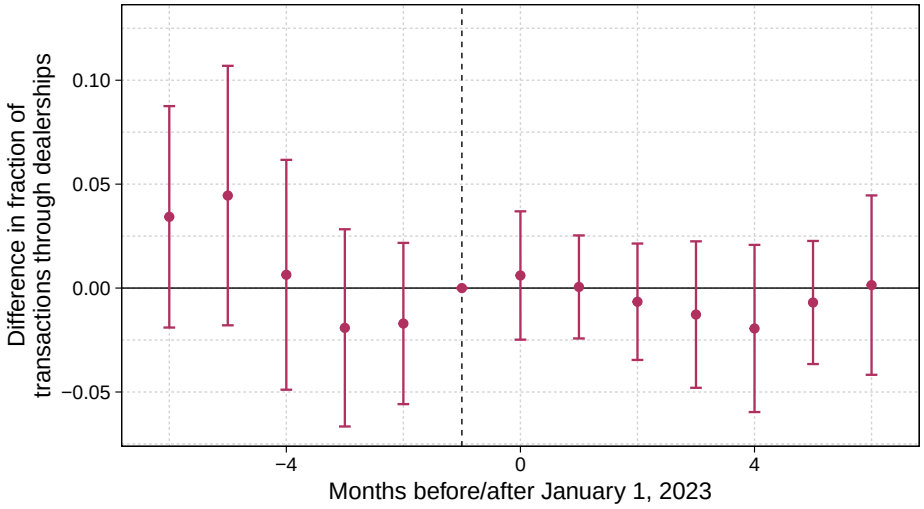
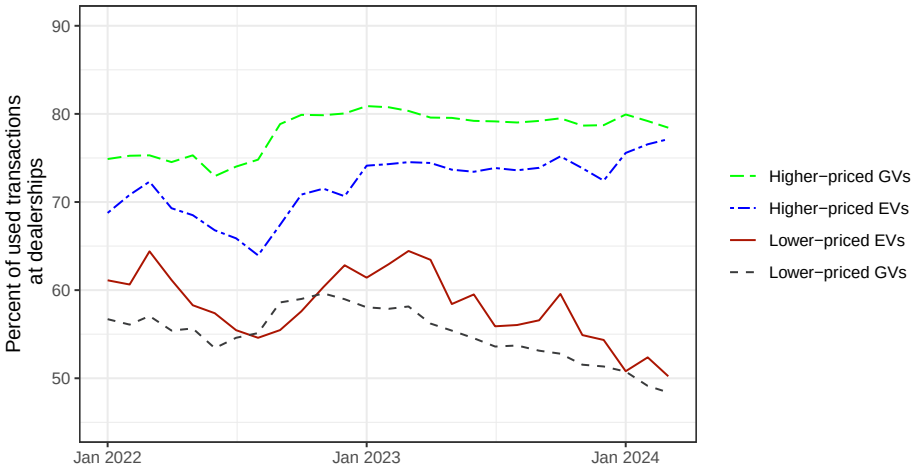


Figure A8: **Dealership Transaction Share by Powertrain and Price**



D.4 Event Study Regression Tables

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

Figure A9: **Dealership Share Triple-Differences Event Study Around January 2024**

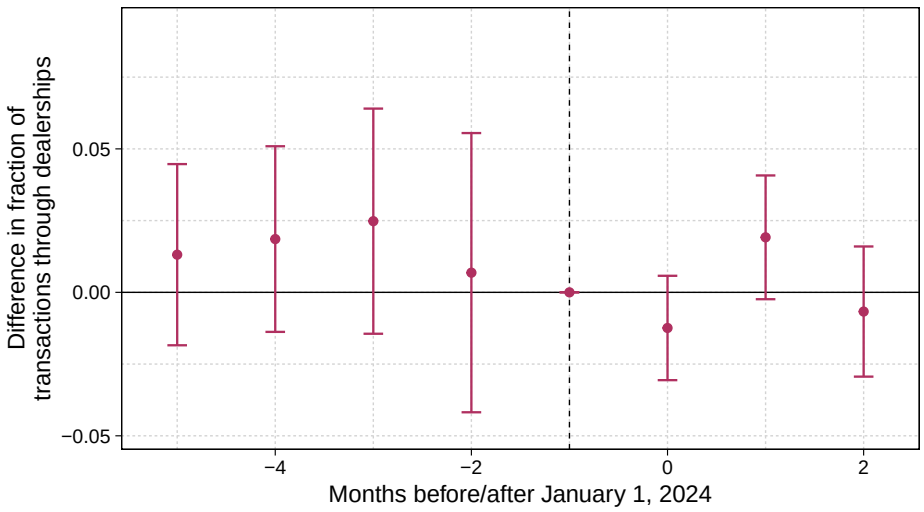


Table A3: **Price, APR, and Buyer Income Effects around January 2023**

	(1) ln(Transaction Price)	(2) APR	(3) Buyer income (000's)
EV × Predicted price <$21k	-0.014	0.5075	0.3591
× After Jan. 2023	(0.0386)	(0.2284)	(0.9066)
ln(Odometer)	-0.1401	1.043	-1.0888
	(0.0059)	(0.047)	(0.0405)
Fixed effects			
Make × Time-to-treat	Yes	Yes	Yes
MY	Yes	Yes	Yes
Model	Yes	Yes	Yes
Dealership	Yes	Yes	Yes
Observations	2,119,347	1,077,535	2,046,227

Notes: Errors are clustered at the model level.

Table A4: **Price, APR, and Buyer Income Effects around January 2024**

	(1) ln(Transaction Price)	(2) APR	(3) Buyer income (000's)
EV × predicted price <$21k	0.0361	0.5024	0.7794
× after Jan. 2024	(0.0224)	(0.1948)	(0.6205)
ln(Odometer)	-0.1775	1.2601	-1.1598
	(0.0060)	(0.0404)	(0.0478)
Fixed effects			
Make × Time-to-treat	Yes	Yes	Yes
MY	Yes	Yes	Yes
Model	Yes	Yes	Yes
Dealership	Yes	Yes	Yes
Observations	1,713,390	846,170	1,580,048

Notes: Errors are clustered at the model level.

Table A5: **Quantity Effects around January 2023**

	(1) Scaled transaction quantity	(2) Dealership %
EV × Predicted price <$21k	-0.2389	-0.0257
× After Jan. 2023	(0.1265)	(0.0161)
Fixed effects		
Make × Time-to-treat	Yes	Yes
MY	Yes	Yes
Model	Yes	Yes
Observations	30,989	29,901

Notes: Errors are clustered at the model level.

D.5 Measuring Excess Mass at $25,000

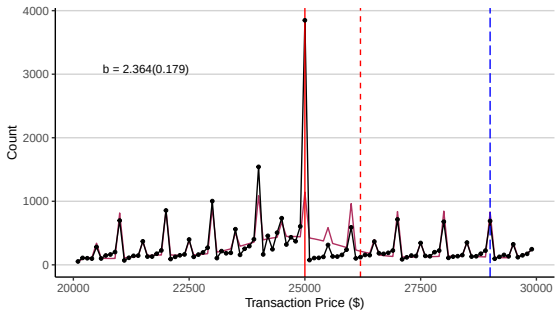
The goal of this section is to quantify the excess mass in the transaction price distribution under $25,000 shown in the descriptive analysis in Section 5.2.

We use an empirical analysis of a tax notch with bunching below based on Kleven and Waseem (2013). This analysis matches a high-order polynomial to the price distribution outside of a small range around $p^* = \$25,000$. We also include round-number fixed effects to the polynomial of best fit for multiples of \$500 and \$1,000 which account for the fact that people more often set prices at round numbers.

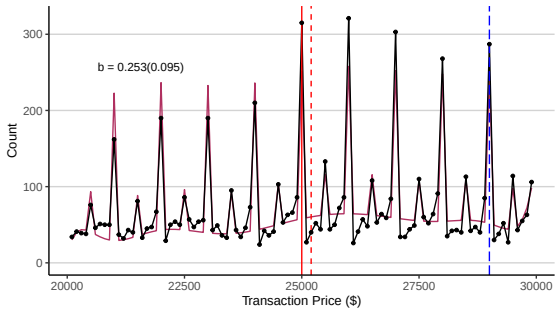
Figure A10 shows an example of this analysis for the transaction price distribution of EVs in 2022 and 2024. The black line shows the values from the data and the solid red line shows the counterfactual distribution constructed as described above. The red dotted lines show the upper bound of the missing mass area, which is constructed so that the missing mass area matches the excess mass at the notch point. The excess mass is calculated from the value found in the data scaled by the expected mass from the counterfactual distribution. In 2024, it is 319 percent of the expected mass. There is a small but positive excess mass level found in 2022, although this is before the policy implementation. This can be attributed to the fact that \$25,000 is a more common price than other multiples of \$1,000. We use the excess mass in 2022 as a baseline level of bunching at \$25,000.

Figure A10: **Bunching Analysis for EVs**

(a) 2024

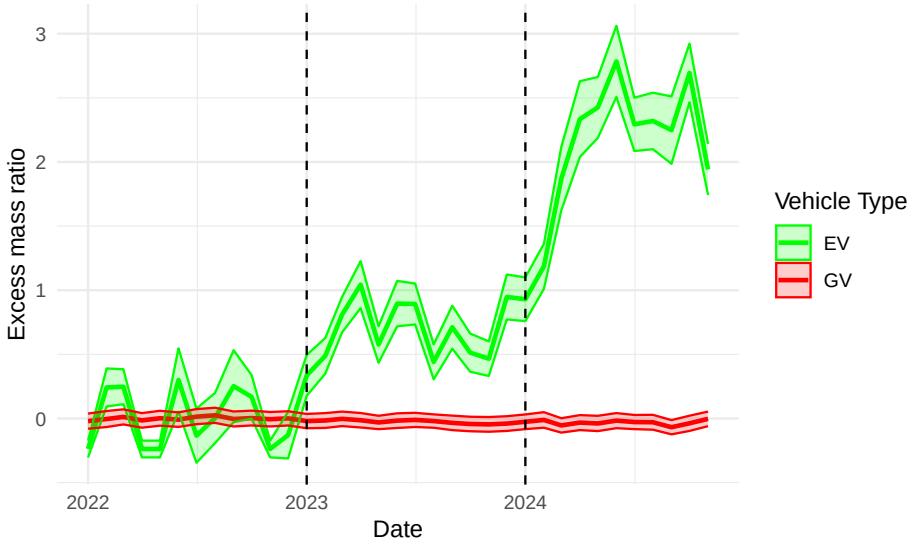


(b) 2022



We perform the bunching analysis on the price distribution in each month for both EVs and GVs. The results in Figure A11 show the monthly excess mass measure net of the baseline 2022 excess mass measure for each vehicle group. We refer to this as the "additional excess mass." The amount of bunching is more volatile for EVs than for GVs even before the policy implementation. In 2023, the additional excess mass for EVs is consistently above 0 and generally hovers between 150 percent and 200 percent. The additional excess mass for EVs jumps above previous levels at the start of 2024 and continues to grow through June of 2024. The additional excess mass for GVs is consistently close to 0 throughout the time period, which lends support to the claim that the changes in bunching stem from the relevant policy changes for EVs.

Figure A11: **Excess Mass by Month**



E Structural Model Estimation Appendix

E.1 Consumer Holding Time Distribution

We use survey data from the 2009 NHTS to obtain a nationally representative sample of the distribution of vehicle holding time in the US. An observation in the survey gives the current length of time each vehicle has been held in months. However, the relevant measure for our model is the total time the vehicle is held before resale or scrappage rounded to years.

We impute the distribution of total holding time h in the pool of vehicle owners I^O from the distribution of current holding time h^c by assuming that consumers are randomly distributed within their holding time at the time of the survey. Of the group of consumers with total holding time h_i, denoted $i \in I^O_{\{h^T=h_i\}}$, there are $|I^O_{\{h^T=h_i\}}|/h_i$ consumers in each current holding year $h^C \in \{1, ..., h_i\}$. The set of consumers with, for example, current holding time $h_i^C = 1$, denoted by $i \in I^O_{\{h_i^C=1\}}$, come proportionally from each total holding time group based on the inverse of the total holding time. We cap maximum holding time at 20 years and remove extreme observations with current holding times greater than 20 years. Then, for all $h_i^C \in \{1, ..., 20\}$ we have

$$|I^O_{\{h^C=h_i^C\}}| = \sum_{h=h_i^c}^{20} \frac{|I^O_{\{h^T=h\}}|}{h}. \tag{110}$$

Given the observed current holding times h_i^c, this yields a unique solution for total holding times h_i in the

consumer pool[10]. We get the distribution by dividing the size of each owner group by the total number of owners in the survey. We smooth this distribution using a 3-year moving average. The computed average maximum holding time is 8.61 years.

We need to further adjust this distribution to capture the distribution of holding times in the buyer pool I^B. Consumers with total holding times $h_i = 1$ will enter the buyer pool 20 times as frequently as consumers with total holding time $h_i = 20$. To adjust the buyer distribution, we take $|I^B_{\{h^T=h_i\}}| = |I^O_{\{h^T=h_i\}}|/h_i$ and then divide by the implied number of buyers in a given period. We assume that the distribution of buyers is stationary over time.

E.2 Future Price Expectations

In our model and counterfactual simulations, consumers are forward-looking and perfectly predict future prices. In the demand estimation, we do not observe the full set of future prices and so must approximate the consumer expectations. We do this by predicting the prices of vehicles in the market as they age by running the following regression:

$$\ln(p_{ja}) = \lambda_j + \beta_a^{EV} EV_j a + \beta_a^{GV}(1 - EV_j)a + \epsilon_{ja}. \tag{111}$$

We allow prices to decrease with age at a different rate across EVs and GVs. We use these results found in Table A6 to predict $\hat{p}_{jya+h_i}$ for each vehicle j at the end of each consumer i's holding time h_i.

Table A6: **Price Prediction Regression**

β_a^{GV}	-0.116	(0.001)
β_a^{EV}	-0.120	(0.004)
Model FE	Yes	

E.3 Moment Conditions in GMM Estimation

As discussed in Section 7.2, we use data from Strategic Vision and the NHTS to calculate the target micro-moments, shown in Table A7.

We match the correlation coefficient between the ages of vehicles at time of purchase for households with two vehicles from the 2009 NHTS to the model-implied covariance of ages of purchased vehicles when households have two choice opportunities. From the sample of two-vehicle households in the 2009 NHTS,

[10]For example, $\frac{1}{20}$ of consumers with $h_i = 20$ have currently held their vehicle for 20 years, so $|I^O_{\{h^C=20\}}| = 20 \times |I^O_{\{h^C=20\}}|$

we also match the share of new vehicle buyers that purchased both current vehicles at age 0 to the model-implied share from two choice opportunities. These differ from moments based on model-implied second choice vehicles because households may purchase the same vehicle type twice.

To understand the relationship between income level and preferences new vs. used vehicles, and vehicle age, we match average vehicle age at time of purchase and share new among consumers with income below \$75,000. We also match the average EV share and purchase price among consumers with income below \$75,000 that purchase a new vehicle.

Given the distribution of consumer incomes and the overall market shares of each vehicle type, using these moments pins down purchasing patterns for both high (>\$75k) and low (<\$75k) income groups. We use the Strategic Vision data, which only contains new vehicle purchases, to find the observed EV share and average purchase price for low income consumers. We use the 2009 NHTS data to find the observed average age and share of new vehicles at time of purchase for low income consumers.

Finally, we match the price elasticity of EVs in aggregate to -2.1 based on Muehlegger and Rapson (2022) and the sum of the squared residuals $\mathbb{E}[\xi_{jmy}^2]$ to 0.

Table A7: **Observed Moments**

Price elasticity of EVs	-2.100
	(0.460)
Correlation coeff. btwn vehicle age of choice opportunity one and two	0.437
	(0.012)
EV second choice share	0.530
	(0.209)
Share of new vehicle buyers that would purchase two new vehicles	0.538
	(0.007)
EV share among buyers w/ income under \$75k	0.030
	(0.001)
Average age at purchase among buyers w/ income under \$75k	6.498
	(0.430)
Average price at purchase among buyers w/ income under \$75k	38,356
	(84.28)
New vehicle share among buyers w/ income under \$75k	0.234
	(0.022)

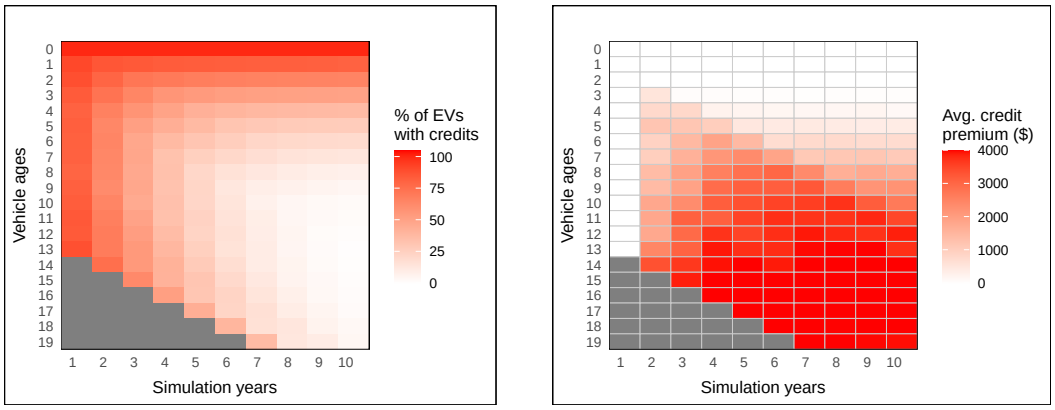
Notes: Estimate and standard error of the price elasticity of EVs taken from Muehlegger and Rapson (2022)

F Counterfactual Results Appendix

F.1 Used EV Credit Premium

We now show the effect of used EV credit premiums across simulation years. Figure A12a shows the percentage of EVs with a remaining credit, which is decreasing over time and with age. Figure A12b shows the average credit premium, which is changing in the opposite pattern.

Figure A12: Used EV Credit Premiums



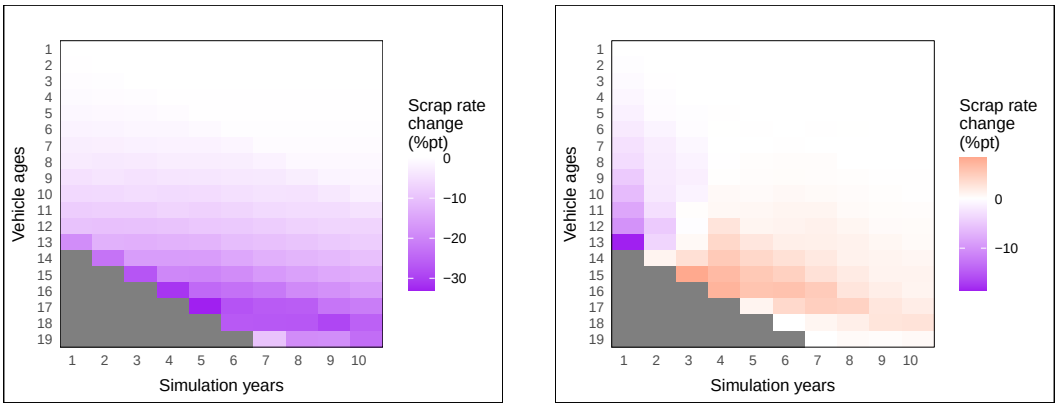
(a) Percent of EVs with remaining credits

(b) Used EV credit premium

F.2 Scrap Probabilities

We now show the change in scrap rates for EVs in the no-restrictions used EV subsidy scenario compared to the no-subsidy baseline. Figure A13a and Figure A13b shows the change for EVs with and without a remaining credit premium, respectively. The scrap rates remain stable for young ages just because the scrap rate is very low in both simulations. We start to see a large decrease in scrap rates for vehicles above the age of 10 with a remaining credit premium, while the scrap rate mildly increases for EVs of similar age without a credit premium.

Figure A13: Changes in Scrap Rates from Used EV Subsidies



(a) Used EVs with remaining credits

(b) Used EVs without remaining credits