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

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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 after 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, each of which identifies a key model parameter.

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 about \$390. 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. We show formally that under certain first-order approximations, the increase in bunching is proportional to the increase in demand from dealership transfer. 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.

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% initially and over 14% 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 simulations, 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. 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.

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 both the incidence of these subsidies and the optimal policy.

In the model, EVs live for two periods. In their first period, new EVs are produced in symmetric imperfect competition, sold at price p_n, and driven by new vehicle buyers. In their second period, the now-used EVs are either resold to used vehicle buyers at price p_u or are scrapped at price p_u. After their second period, all remaining used vehicles are scrapped at zero price.

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 $\{\tau_n, \tau_u\}$, 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. Vehicle scrappers are not eligible.

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, we assume that aggregate EV demand is (locally) linear and that eligible and ineligible buyer types have the same demand function. Third, we assume no substitution between new and used vehicle markets. Fourth, new vehicle buyers use discount factor δ to trade off resale prices relative to purchase prices. Under these assumptions, new vehicle demand is $D_n \coloneqq D_n(p_n - \mu\tau_n - \delta p_u)$, and used vehicle demand is $D_u \coloneqq D_u(p_u - \mu\tau_u)$, with $D_n' \leq 0$ and $D_u' \leq 0$.

Scrappage demand is $R \coloneqq R(p_u)$, with $R' \leq 0$. We assume that scrappers receive a constant marginal scrap value of v_s per vehicle, thus their profits are defined as $R(p_u) \cdot (v_s - p_u)$. We also assume that scrappage is linear in p_u.

The new good is produced at constant marginal cost c and sold in symmetric imperfect competition with exogenous conduct parameter $\theta \in [0,1]$, following a special case from Weyl and Fabinger (2013). Each firm's first-order condition is $p_n - c = \theta \frac{D_n}{-D_n'}$. Aggregate supply is denoted $S \coloneqq S(p_n)$.

The equilibrium is a set of prices $\{p_n, p_u\}$ such that (i) consumers and firms optimize, (ii) new good buyers correctly forecast the resale price p_u, and (iii) markets clear, so $S = D_n = D_u + R$.

Define W as total surplus over the life cycle of one generation of EVs. We assume that the social planner uses the same discount factor δ as consumers and that the government can use lump-sum taxes and transfers, so the marginal cost of public funds equals one. W is the discounted sum of consumer surplus (summing both eligible and ineligible types), producer surplus, and positive externalities net of government spending:

$$\begin{aligned}
&W(\tau_n, \tau_u, \mu) = \\
&\quad \underbrace{\mu \cdot \int_{p_n-\tau_n-\delta p_u}^{\infty} D_n(x)dx + (1-\mu) \cdot \int_{p_n-\delta p_u}^{\infty} D_n(x)dx + D_n(p_n - \mu\tau_n - \delta p_u) \cdot (p_n - c + \phi)}_{\text{New EV CS, PS, and externality}} \\
&- \underbrace{\mu\tau_n D_n(p_n - \tau_n - \delta p_u)}_{\text{New EV subsidy}} + \delta \underbrace{\left[\mu \cdot \int_{p_u-\tau_u}^{\infty} D_u(x)dx + (1-\mu) \cdot \int_{p_u}^{\infty} D_u(x)dx + D_u(p_u - \mu\tau_u) \cdot (\phi)\right]}_{\text{Used EV CS and externality}} \\
&\qquad - \underbrace{\delta\mu\tau_u \cdot D_u(p_u - \tau_u)}_{\text{Used EV subsidy}} + \underbrace{\delta R(p_u) \cdot (v_s - p_u)}_{\text{Scrappers' Profits}} \qquad (1)
\end{aligned}$$

3.2 Optimal Policy

The total surplus maximizing policy involves full eligibility $\mu = 1$. Explained intuitively, we assume a linear cost of the policy, linear benefit of the policy (ϕ is constant), and linear approximations of demand and supply. Combined, this makes the marginal effect of μ roughly linear, implying a corner solution. It is a standard result that there exists an optimal tax scheme that raises total surplus compared to no policy. With this preface, we present the optimal subsidy policy.

Lemma 1 (Optimal subsidies): The total surplus-maximizing subsidies are

$$\begin{aligned}
\mu^* &= 1 \\
\tau_n^* &= p_n - c + \phi + \delta \cdot [v_s - p_u] \qquad (2) \\
\tau_u^* &= \phi - [v_s - p_u]
\end{aligned}$$

Proof: see Appendix A.1.

The optimal policy is a direct extension of the standard Pigouvian optimal subsidy - subsidize the market by the externality plus the markup. The difference is that in our model there are two markups to consider: the manufacturer's and the scrapper's. Note that any vehicle purchased by used EV demand will not receive the markup. Thus, in essence, used demand imposes a negative externality of $[v_s - p_u]$. Therefore, by Pigouvian logic, the total used subsidy should be the positive externality ϕ minus the negative externality $[v_s - p_u]$, which is our result. Alternatively, on the new demand side, the scrapper's profit is seen as a positive externality, so it is subsidized at the discount rate δ.

3.3 Incidence

We now consider incidence: the effect of marginal subsidy changes on equilibrium prices. First, we consider short-run effects of a surprise used EV subsidy. Then, we consider the steady-state effects of new and used EV subsidies.

3.3.1 Short-Run Incidence with Fixed Supply

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 are no longer in production. We can predict this short-run incidence in our model by considering the effect of a marginal increase in τ_u after D_n has been fixed at D_n^*, giving fully inelastic used vehicle supply. The used vehicle market clearing condition is then $D_n^* = D_u(p_u - \mu\tau_u) + R(p_u)$. Totally differentiating this condition and re-arranging gives

$$\frac{dp_u}{d\tau_u} = \frac{\mu D_u'}{D_u' + R'}. \tag{3}$$

If scrappage is fully inelastic, as would approximately be the case for late-model used vehicles that are rarely scrapped, this simplifies to $\frac{dp_u}{d\tau_u} = \mu$. Thus, in that special case, the used vehicle tax credit would increase used vehicle prices by the credit amount times the share of buyers who are eligible. If scrappage is not fully inelastic, then higher used EV prices reduce scrappage, which moderates the equilibrium effects of the credit on EV prices.

This has different implications for different consumer groups. If some consumers are ineligible ($\mu < 1$) or scrappage is not fully inelastic ($R' < 0$), then the used vehicle price increases less than one-for-one with the subsidy. Thus, 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.

3.3.2 Long-Run Steady-State Incidence

In the long run, equilibrium new EV demand adjusts in response to predicted changes in EV resale prices. We now derive this steady-state incidence.

Proposition 1 (Incidence): the effects of marginal subsidy changes on steady-state equilibrium prices are

$$\begin{aligned} \frac{dp_n}{d\tau_n} &= \frac{\theta\mu(D_u' + R')}{(1+\theta)(D_u' + R') + \delta D_n'} \geq 0, \quad & \frac{dp_n}{d\tau_u} &= \frac{\theta\delta\mu D_u'}{(1+\theta)(D_u' + R') + \delta D_n'} \geq 0 \\ \frac{dp_u}{d\tau_n} &= \frac{-\mu D_n'}{(1+\theta)(D_u' + R') + \delta D_n'} \leq 0, \quad & \frac{dp_u}{d\tau_u} &= \frac{(1+\theta)\mu D_u'}{(1+\theta)(D_u' + R') + \delta D_n'} \geq 0. \end{aligned} \tag{4}$$

Proof: see Appendix A.2.

The comparative statics are intuitive and analogous to the short-run case above. The new EV subsidy increases the new EV price and decreases the used EV price, because it increases demand for new EVs and thus increases the supply of used EVs. The used EV subsidy increases both new and used EV prices, because it increases demand for used EVs and thus increases the resale value for new EVs. Unless all buyers are eligible and demand and scrappage are both fully inelastic, the subsidies increase market prices less than one-for-one. Thus, except in that special case, 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 eligibility share μ appears once in the numerator in each equation in Proposition 1. Thus, as μ decreases, the price effects also decrease, because the effects on demand also decrease. 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.

A corollary to Proposition 1 is that if scrappage is fully inelastic, then discounted new EV subsidies have the same effect as used EV subsidies on equilibrium subsidy-inclusive prices:

Corollary 1 (Symmetry): If $R' = 0$:

$$\begin{aligned} \delta \cdot \frac{d(p_n - \mu\tau_n - \delta p_u)}{d\tau_n} &= \frac{d(dp_n - \mu\tau_n - \delta p_u)}{d\tau_u} \\ \delta \cdot \frac{d(p_u - \mu\tau_u)}{d\tau_n} &= \frac{d(p_u - \mu\tau_u)}{d\tau_u}. \end{aligned} \tag{5}$$

Proof: see Appendix A.3.

The intuition for this corollary is as follows. The used and new markets are directly linked by used prices entering new demand with a discount factor δ. This implies that only a δ portion of any used subsidy will be felt in the new market. Therefore, the effect of a discounted new subsidy will equal that of used subsidies. Beyond discounting, this is just as in the textbook case of subsidizing supply versus demand, statutory incidence is independent of economic incidence.

Note that this corollary implies that if $R' = 0$, a tax change where $\delta\Delta\tau_n = -\Delta\tau_u$ will have no effect on subsidy-inclusive prices. Therefore, an interesting application of this corollary is that if scrappage is perfectly inelastic, there will exist a continuum of optimal policies.

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 decrease in the discount factor δ, muting the effects of the used EV credit on new vehicle prices.

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 transactions, and other realistic forces.

4 Data

We use transaction-level microdata covering July 2021 to May 2024 from Cox Automotive, including both new and used transactions. These data cover about 44 and 39 percent of new and used transactions, respectively, through dealerships in 2022 through early 2024. We observe the week of the transaction, the VIN, lease terms, transaction price (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 to April 2024. We observe monthly sales of new and used vehicles by the intersection of make, model year, vehicle model and trim level, buyer type (individual, organization, or government), and seller type (dealership or individual). In addition, we observe the total stock of registered vehicles in Q3 of 2022 and 2023.

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 for price and mileage by removing the upper and lower 0.5 percent.

In addition to the above, we impose further restrictions for just the event study data. Specifically, we exclude all vehicles older than the 2011 model year. Our rationale is that the oldest EVs in the data are of model year 2011; therefore, any older GVs are not a comparable group for an event study. We also exclude model-by-model year 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-model year 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.

For the structural model, we aggregate transactions to the car type level for each make and fuel type. A car type consists of two parts: a car segment which is either car, SUV, or pickup as well as a size component based on curb weight. An example observation is "SUV - medium." In an effort to reduce our choice set cardinality, we group minivans under SUVs and fullsize vans under trucks. In addition, we explicitly exclude sports cars due to their overall small transaction share and the differences in market trends compared to the overall car market. The size definition is constructed manually by examining the distribution of curb weights for a given make-segment and then picking zero to two cutoffs based on the size of the observed dispersion.

We impose a single car type for each model across all model years to more accurately represent changes in vehicle stocks over time. Grouping observations at the car type level is useful because manufacturers change vehicle models relatively frequently, making sharp discontinuities in vehicle stocks at the level of make, model, and model year. We also account for this directly by grouping renamed models across time under a common model name.

5 Reduced-Form Evidence: Effects on Vehicle Prices

This section aims to assess the effects of the Used Clean Vehicle Credit on vehicle prices. The timing of the policy implementation allows us to separately estimate two key parameters characterizing important aspects of resale markets and tax credit policy: tax credit pass-through and the value of dealership transfer.

5.1 January 2023 Event: Tax Credit Price Effect

The implementation of the tax credit occurred on January 1, 2023. The price effect from this policy event 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. As 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.

This section presents a triple-difference event study comparing cheap and expensive EVs and GVs around the implementation of the tax credit.

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 before 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_{ikyt} as the price of transaction i of vehicle model k and model year y in month t. We include vehicle model by model year fixed effects λ^{ky}, month-of-year fixed effects λ^{m_t}, and dealership fixed effects λ^{d_i}. odo_{ikyt} is the odometer reading of the vehicle in the transaction, and P_t represents the number of periods since the start of the sample period. We base price predictions on

$$\ln(p_{ikyt}) = \lambda^{ky} + \lambda^{m_t} + \lambda^{d_i} + \beta \cdot odo_{ikyt} + \sum_{s=2011}^{2021} \gamma_s \mathbb{1}\{y = s\} \cdot P_t + \epsilon_{ikyt}. \tag{6}$$

The term $\sum_{s=2011}^{2021} \gamma_s \mathbb{1}\{y = s\} \cdot P_t$ allows for a time trend in prices as a vehicle model year ages and allows this trend to vary by model year. 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 $\hat{p}_{ikyt} = exp(\widehat{ln(p_{ikyt})})$.

We estimate a triple-difference event study of the implementation of the Used Clean Vehicle Credit. The pre-period contains the months of July through December of 2022. The post-period begins on January 1, 2023 and extends through July 2023. 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_k is the treatment indicator based on fuel type, λ^t is the period fixed effect, $\lambda^{make_k} \times \lambda_t$ is an interaction between fixed effects for the make of vehicle k and the month t. We estimate the triple-differences event study graphs using

$$\begin{aligned}\ln(p_{ikyt}) = &EV_k + G_i + EV_k \times G_i + G_i \times \lambda^t + EV_k \times \lambda^t \\ &+ G_i \times EV_k \times \lambda^t + (\lambda^{make_k} \times \lambda^t) + odo_{ikyt} + \lambda^k + \lambda^y + \lambda^{d_i} + \epsilon_{ikyt}. \end{aligned} \tag{7}$$

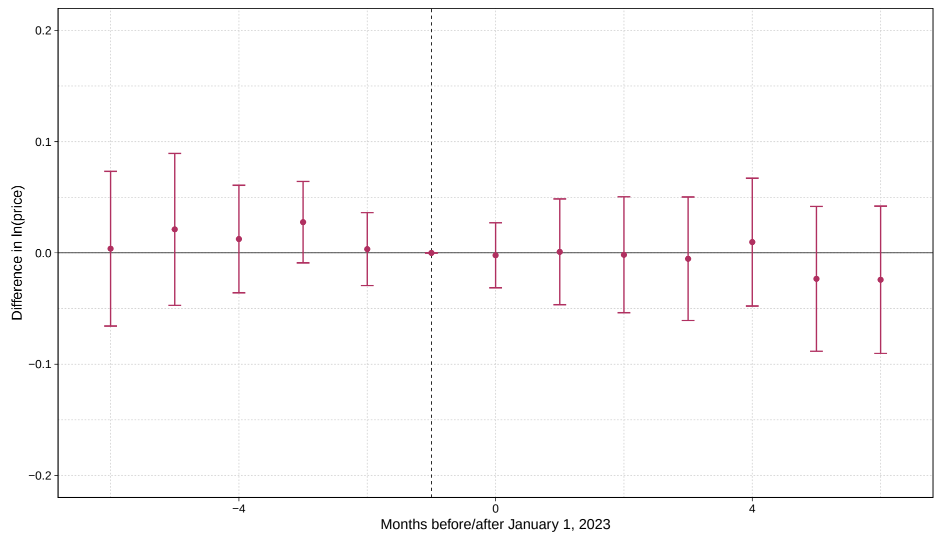
We include the interaction between vehicle make and time period to account for trends across manufacturers. We cluster standard errors at the model by model year level. The sample includes used vehicle transactions from the Cox data as described in Section 4. We exclude new vehicles because their prices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

5.1.2 Results

Figure 1 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 A2, we reject price increases of more than \$390 dollars for a vehicle that would have cost \$20,000 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.

Figure 1: **Price Effect of Used Clean Vehicle Credit on Used EVs**



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 this policy announcement within the first 6 months of implementation, and consumer responses may differ in the long run as dicussed above. Third, used GVs and relatively expensive 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.1 shows that there is no evidence of such anticipation effects.

5.2 January 2024 Event: Value of Dealership Transfer

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. Consumers may prefer the dealership transfer because they can receive the benefit sooner and avoid the cost of filing additional paperwork with their taxes. This section compares the bunching of transactions below the $25,000 price threshold across years to understand how much consumers value the dealership transfer.

Figure 2 shows the sale price distribution for 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 mass under $25,000 in 2023, and considerably higher excess mass 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 excess mass 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 2: **Sale Price Distribution for Used Vehicles**

(a) EVs (b) GVs

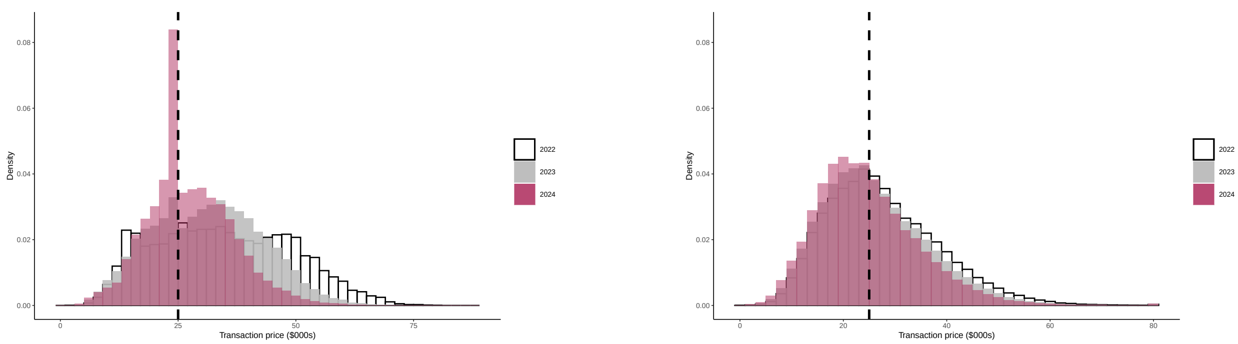
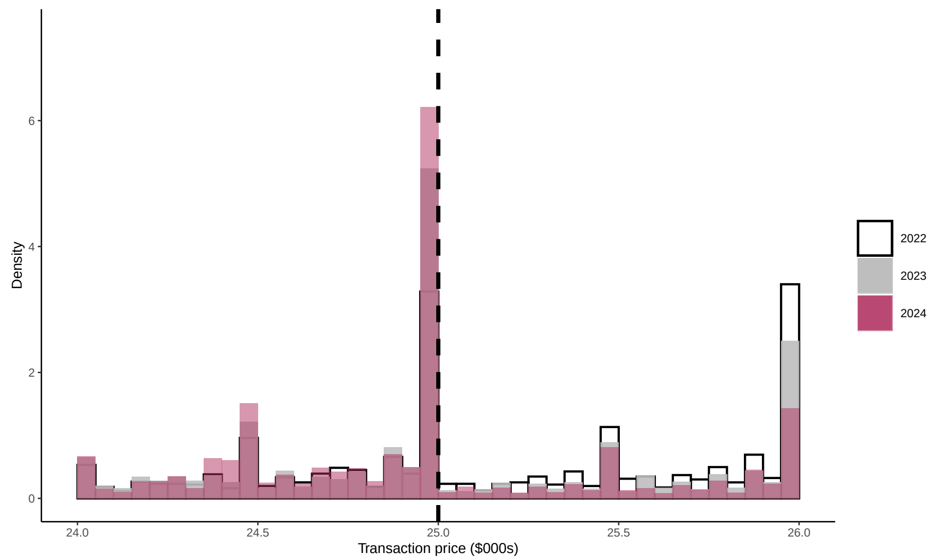


Figure 3 shows the portion of the price distribution just above and below $25,000. We can see that bunching generally occurs at round numbers, and the density right at $25,000 in 2024 exceeds the 2023 value. We see additional excess mass around and below $24,500 in 2024 compared to both 2022 and 2023.

Figure 3: **Used EV Sale Price Distribution Around $25,000**



Appendix B shows formally that under first-order approximations, the change in the amount of bunching in 2024 versus 2023 identifies the increase in demand from dealership transfer. Appendix D.3 estimates that bunching increased by several multiples by mid-2024 relative to 2023, which implies that dealership transfer had large effects on demand.

Appendix D.1.4 shows that there is no change in the share of EV transactions through dealerships in either 2023 or 2024.

6 Structural Model

Each period t, consumer i makes a static decision to purchase a vehicle j of age a. Consumer types are characterized by income and the length of time they own a given vehicle. Vehicles are characterized by their make, body style, size segment, and fuel type. At the end of the holding period, consumers either re-sell their vehicle in the used vehicle market or choose to scrap the vehicle.

Supply of new vehicles is determined by new car prices set by profit-maximizing automakers. Quantities of used vehicles are 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 cars transferred from institutions, including government and rental car companies, to individuals. New car prices are determined by automakers to maximize their profits, while used car 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 $\widetilde{u}_{ija}$ denote the utility of consumer i from owning vehicle j with 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 at period t is given by

$$U_{ijat} = \sum_{k=0}^{h_i-1} \rho^k \widetilde{u}_{ija+k} + P_{ijat} - \rho^{h_i} P_{ija+h_i,t+h_i} \tag{8}$$

where ρ is the time discount factor, P_{ijat} represents the price disutility for consumer i from purchasing vehicle j of age a in period t and $-\rho^{h_i} P_{ija+h_i,t+h_i}$ is the benefit of reselling or scrapping the vehicle at the end of the holding period. We parameterize the one-period utility as

$$\widetilde{u}_{ija} = X_{ja}\beta_i + \xi_{ja} + \beta_i^a a + \varepsilon_{ija} \tag{9}$$

where X_{ja} is a vector of vehicle characteristics, β_i^a is an age disutility parameter, and ε_{ija} is an idiosyncratic preference shock following the type I extreme value distribution.

If we assume that each consumer draws ε_{ija} once for the whole holding period, we can write the utility in the second period of the holding time as $\widetilde{u}_{ija+1} = \widetilde{u}_{ija} + \beta_i^a$, 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 can then rewrite the present value of purchasing vehicle j as

$$U_{ijat} = \sum_{k=0}^{h_i-1} \rho^k \widetilde{u}_{ija} + \sum_{k=1}^{h_i-1} \rho^k \beta_i^a + P_{ijat} - \rho^{h_i} P_{ija+h_i,t+h_i} \tag{10}$$

Consumers' choice sets consist of all vehicles j such that $a_j + h_i \leq \bar{a}$ where $\bar{a}$ is the oldest possible age for a vehicle. The age disutility depends on the consumer's holding time and price disutility depends on income.

Lastly, we normalize the utility from the outside option as $u_{i0} = 0$. Since there is a single logit error draw ε_{ija} for one utility flow, a consumer opting for the outside option will not have a car for the entire holding period. There is no option value in refraining from purchasing a vehicle in period t.

6.2 Scrappage Decision

We assume that the consumer scrap decision is model-specific and depends on the resale price p_{jat} and vehicle age. If the resale price for vehicle j of age a in period t is higher, a consumer is less likely to scrap the vehicle in the next period and more likely to resell it. Following Bento et al. (2009), we express the scrap rate at the end of the holding period as

$$g_{ja}(p) = \zeta_{ja} \cdot (p)^{\eta_p} \tag{11}$$

where η_p represents the price elasticity of the scrap probability.

6.3 Expected Rent

We define the price disutility of purchasing vehicle j of age a as follows:

$$P_{ijat} = \alpha_i p_{jat} \tag{12}$$

Here, α_i is the price coefficient for consumer i. The benefit of reselling or scrapping the vehicle at the end of the holding period is:

$$P_{ija+h_i,t+h_i} = -\alpha_i r_{ijat} \tag{13}$$

where r_{ijat} is the resale or scrap value of vehicle j of age a after consumer i's holding period. We can now rescale Equation (10) to define the per-period individual utility as

$$\begin{aligned} u_{ija} &= \widetilde{u}_{ija} + \beta_i^a \left(1 - \frac{1}{\sum_{k=0}^{h_i-1} \rho^k}\right) + \alpha_i \frac{p_{ja} - \rho^{h_i} r_{ija}}{\sum_{k=0}^{h_i-1} \rho^k} & (14) \\ &= \widetilde{u}_{ija} + \beta_i^a A_{ija} + \alpha_i B_{ija} & (15) \end{aligned}$$

where A_{ija} is the adjustment factor for vehicle aging and B_{ija} is the average per-period rent that consumer i pays. Finally, we express utility for individual i purchasing vehicle j of age a as

$$u_{ija} = X_{ja}\beta_i + \xi_{ja} + \beta_i^a(a + A_{ija}) + \alpha_i B_{ija} + \varepsilon_{ija} \tag{16}$$

6.4 Consumer Expectation on Future Prices

The expected future value is:

$$r_{ijat} = \left[1 - g_{ja+h_i}(\widetilde{p}_{ja+h_i,t+h_i})\right] p_{ja+h_i,t} + g_{ja+h_i}(\widetilde{p}_{ja+h_i,t+h_i})\, \underline{p}_j \tag{17}$$

where $\widetilde{p}_{ja+h_i,t+h_i}$ is the consumer's expectation on the future price after the holding period. $\underline{p}_j$ is the scrap value of model j. In this study, we explore two cases based on how consumers form their expectations about future resale prices. In the first case, consumers are myopic, assuming future prices will be the same as current prices: $\widetilde{p}_{ja+h_i,t+h_i} = p_{ja+h_i,t}$. In the second case, consumers are forward-looing, and thus, the expected price is the same with the future equilibrium prices: $\widetilde{p}_{ja+h_i,t+h_i} = p_{ja+h_i,t+h_i}$.

6.5 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 $\{p_{jat} | a = 0,\ j \in J_{ft}\}$, where J_{ft} is the product offerings by firm f in period t, to maximize its profit:

$$\pi_{ft} = \max_{\{p_{jat}|a=0,\ j\in J_{ft}\}} \sum_{j\in J_{ft}} (p_{j0t} - mc_j)\, Q(\boldsymbol{p}_{a=0,t},\ \boldsymbol{p}_{a>0,t},\ \boldsymbol{q}_{a>0,t}) \tag{18}$$

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.

6.6 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 $\Omega^j_{a1} \times (1 - g_{ja})$. The supply of used vehicles from institutions is assumed to be exogenous in this study. It varies over time based on the institutions' new vehicle purchases, which are fixed, and their current vehicle stocks across models and ages.

6.7 Update Rule of COM

A next period COM is determined by car onwers 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 and Calibration

7.1 Consumer Holding Time Distribution

In the California DMV data, we observe the dates of all registered transactions for each vehicle. Computing the interval length between consecutive transactions, we obtain the holding time in months. The California DMV data does not track individual consumers, so we obtain the distribution of how long a vehicle has been owned by one owner, instead of how long consumer owned their vehicle. We therefore utilize vehicle transaction histories in California to derive the holding time distribution. Let c_k represent the number of cars traded after k years from the last transactions. The goal is to infer the holding time distribution of consumers using these car transaction frequencies. Here, we add a simple adjustment. Consumers with a 1-year holding time will occur twice as often on the transaction date as those with a 2-year holding time.

Similarly, consumers with a holding time $h1$ will appear $h2/h1$ times more frequently than those with a holding time of $h2$. Thus, the distribution of consumers with holding times ranging from 1 to T should be proportional to the following ratios:

$$\text{\# of consumers with holding period of 1 year : 2 years : \dots : T years} = c_1 : 2 \cdot c_2 : \dots : T \cdot c_T \tag{19}$$

The holding time distribution derived in this manner from the car transaction data yields an average consumer holding time of around 4.5 years.

7.2 Scrap Probability and Scrap Value

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

$$y_{jat} = \frac{N_{jat} - N_{ja+1,t+1}}{N_{jat}} \tag{20}$$

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 two years but rather the probability of scrapping the vehicle conditional on the owner reaching the end of the holding period. 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_{ja} 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,

$$g_{jat} n_{jat} = N_{jat} - N_{ja+1,t+1} = y_{jat} N_{jat} \tag{21}$$

where $N_{jat} - N_{ja+1,t+1}$ is the number of scrapped vehicles. Since we observe all the values in Equation (21) 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:

$$g_{jat} = exp(\zeta_j + \eta_a a_j + \epsilon_{jat}) \cdot (p_{ja})^{\eta_p} \tag{22}$$
$$\Rightarrow \; ln(g_{jat}) = \zeta_j + \eta_a a_j + \eta_p ln(p_{ja}) + \epsilon_{jat}$$

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 1 presents the OLS estimates of the scrap parameters. The price elasticity of scrap rates is similar to that found in Jacobsen and Benthem (2015), where the scrap elasticity is estimated at -0.7.[1] However, there could be an endogeneity

[1] Jacobsen and Benthem (2015) use the yearly scrap rates y_{jat} instead of the scrap rates after holding periods. However, Equation (21) shows that the price elasticity of scrap rates is identical for both cases

$$\frac{dln(y_{jat})}{dln(p_{jat})} = \frac{dln(g_{jat})}{dln(p_{jat})} = \eta_p \tag{23}$$

Table 1: **Scrap Parameter Estimation**

	(1)	(2)
	$\ln(g_{jat})$	$\ln(g_{jat})$ + 0.7 ln(price)
Age	0.059	0.069
	(0.014)	(0.003)
ln(price)	−0.795	–
	(0.128)	
Model FE	Yes	Yes
Observations	3,305	3,305
Adjusted R^2	0.541	0.290

issue as the price p_{jat} might be correlated with the scrappage shock ϵ_{jat}. Thus, we calibrate $\eta_p = -0.7$ from Jacobsen and Benthem (2015) and estimate the remaining parameters for our main specification as shown in the second column. Lastly, we set the scrap value $\underline{p}_j$ equal to zero for all models.

7.3 Demand Parameters

From our utility specification in Equation 16, we specify a linear utility over vehicle types and nonlinear utility over rent, age, and fuel type. We need to estimate $(\alpha, \beta_0, \beta_a, \sigma_{EV}, \sigma_a, \lambda_j)$ in the following equation:

$$\begin{aligned} u_{ija} &= \beta_0 + \lambda_j + \xi_{ja} + \beta_a(a + A_{ija}) + \sigma_{EV}\nu_{EV,i}\mathbb{1}\{EV_j = 1\} + \sigma_a\nu_{a,i}a + \frac{\alpha}{inc_i}B_{ija} + \varepsilon_{ija} \qquad (24) \\ &= \delta_{ja} + \beta_a(a + A_{ija}) + \sigma_{EV}\nu_{EV,i}\mathbb{1}\{EV_j = 1\} + \sigma_a\nu_{a,i}a + \frac{\alpha}{inc_i}B_{ija} + \varepsilon_{ija} \end{aligned}$$

where λ_j represents the vehicle type fixed effect, ν_i is the unobserved consumer preference over EVs taken from a standard normal distribution, EV_j is an indicator for vehicle type j being an EV, and inc_i is the simulated income of consumer i. Given that price sensitivity is defined as $\alpha_i = \alpha/inc_i$, wealthier consumers are less price sensitive than those with lower incomes. We set $\rho = 0.9$ to calculate the age adjustment factor A_{ija}, and use depreciation rates and scrappage parameters to compute the average rent B_{ija}.

We estimate β_{EV} and β_a using the generalized method of moments (GMM). We use the following moment conditions in the estimation:

$$\mathbb{E}[\xi^2] = 0 \tag{25}$$

$$\mathbb{E}\left[\frac{\sum_{j\in J_{EV}}\sum_{q\in J_{EV}\setminus\{j\}} s^2_{iq|j}}{\sum_{j\in J_{EV}} s_{ij}} - \int_{\mathbf{z}}\int_{\nu} \Pr(y^2 \in J_{EV}|y^1 \in J_{EV}, \theta)d\mathbf{z}d\nu\right] = 0 \tag{26}$$

where $\frac{\sum_{j\in J_{EV}}\sum_{q\in J_{EV}\setminus\{j\}} s^2_{iq|j}}{\sum_{j\in J_{EV}} s_{ij}}$ is the observed share of consumers with a second choice vehicle of an EV conditional on their first choice vehicle being an EV and $\int_{\mathbf{z}}\int_{\nu} \Pr(y^2 \in J_{EV}|y^1 \in J_{EV}, \theta)d\mathbf{z}d\nu$ is the model-implied moment. We follow Berry, Levinsohn, and Pakes (1995) to recover the mean utilities δ_{ja} by matching the observed and model-predicted market shares of vehicles.

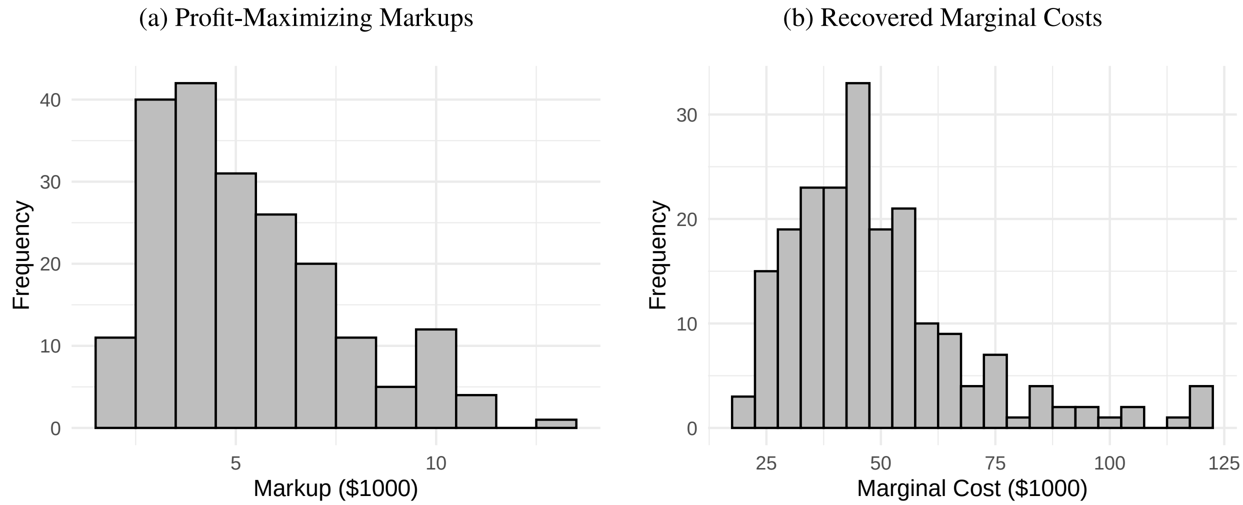
Conditional on these parameters, we estimate α by matching the price elasticity of EVs in aggregate to -2.1. This is the price elasticity of demand for EVs found from quasi-experimental variation in EV subsidies in California in Muehlegger and Rapson (2022). We iterate between this GMM estimation and the price-elasticity matching until the parameter values are stable. Then, we regress the implied mean utilities on the vector of vehicle characteristics to estimate the remaining utility parameters. Table 2 shows the estimation results.

Table 2: **Estimated Demand Parameters**

Price/Income (α)	-28.78
	(–)
Age (β_a)	$-5.26\text{e}{-5}$
	(–)
EV random coefficient (σ_{EV})	4.49
	(–)
Age random coefficient (σ_a)	$-2.33\text{e}{-4}$
	(–)
Constant (β_0)	-3.16
	(0.387)
Model FE	Yes
Observations	2,545

Using the estimated demand model, we compute the profit-maximizing markups for automakers and recover the marginal costs of new vehicle production.

Figure 4: **Markups and Marginal Costs of New Car Production**



7.4 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 model year 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 model year 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 model year level, rather than the model level. This choice stems from the incomplete range of model years 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 now 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 vehicle market non-stationary. In the year of the policy introduction, the elements of the $\widetilde{\Omega}^j$ matrix are all zeros. However, as the years pass, the elements in Ω^j become smaller, while $\widetilde{\Omega}^j$ contains larger and larger numbers.

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. A credit premium is positive but cannot exceed the value of used EV credit, which is \$4,000. It is determined by both the demand and supply of used EVs. If the proportion of used vehicle transactions that are eligible for the credit is high, then the premium also becomes higher. For example, a 3-year-old Tesla Model X, whose new price exceeds \$100,000, will have a relatively low used credit premium. Potential buyers tend to be households with income levels exceeding the IRA threshold. With fewer potential eligible buyers, the pass-through rate of the consumer tax credit to the sellers should correspondingly be lower. Also, it will take several years for its price to drop below \$25,000, making it eligible for the credit, and thus, a greater time discount should be applied. Additionally, premiums depend on the supply of used vehicles. 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.

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 equilibrium, 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
3) **Used EV credit premiums**: clear the used vehicle markets within the same models

Here, the used vehicle supplies are determined by the previous COM and the scrap probabilities. After we compute the equilibrium in period t, we update the COM following the rules explained below. Then, we repeat the process of simulating short-run equilibria until we have the full set of equilibria.

8.3 Simulation Steps for Myopic Consumers

The goal of a counterfactual simulation is to find the stack of multiple single-year equilibria. Since there are three sets of equilibrium prices (new car prices, used car prices, and credit premiums), we need to establish a nested simulation structure. In the inner loop, we search for the credit premiums that adjust the demand ratio for EVs with and without credits for each model. In the outer loop, we search for the used car prices that clear the used car market and the new car prices that maximize firm profits, given the credit premiums.The following details the simulation steps:

1. For simulation year t, given car prices p_{j0t} search for the credit premiums l_{jat} that satisfy the following conditions:
$$D_{jat} : \widetilde{D}_{jat} = (1 - g_{jat}) \cdot \Omega^{jt}_{a1} : (1 - \widetilde{g}_{jat}) \cdot \widetilde{\Omega}^{jt}_{a1} \text{ for all } j \text{ and } a \tag{27}$$
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.

2. Given the credit premiums, search for the used car prices p_{jat} for $a > 0$ such that
$$D_{jat} + \widetilde{D}_{jat} = (1 - g_{jat}) \cdot \Omega^{jt}_{a1} + (1 - \widetilde{g}_{jat}) \cdot \widetilde{\Omega}^{jt}_{a1} \text{ for all } j \text{ and } a > 0 \tag{28}$$
and for the new car prices that satisfy the first-order conditions of firms' profit maximization.

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.

8.4 Simulation Steps for Forward-Looking Consumers

For the forward-looking consumer case, rent depends on consumers' expectations of future equilibrium prices and premiums. We assume consumers are rational, meaning their 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 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.

We start with consumers expectations on equailibrium prices and premiums in the scond simulation year, the third simulation year, ..., and in the T simulation year. Based on these expectations, we find the equilibrium prices as in the previous subsection for T years. We replace consumers expectations using the equilibrium prices and premiums. Then, find again the equilibrium prices for T years. We repeat this until the consumers expectations and realized equilibrium prices and premiums become close enough.

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 in the previous subsection. Next, we update consumers' expectations with the actual equilibrium prices and premiums. We iterate this process until consumers' expectations converge to the realized equilibrium prices and premiums.

8.5 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 Next Steps

Equivalence Between New and Used EV Subsidies in a Steady State The first focus of our next steps is to explore the conditions under which subsidies for new and used EVs produce equivalent outcomes in the long run. As discussed in Section 3.3.2, new and used EV subsidies yield identical equilibrium outcomes in the steady state when vehicle scrap rates are exogenous (i.e., unaffected by prices). We will first check whether we can acheive this equivalence using counterfactual simulations with estimated structural model.

Factors Breaking the Equivalence between New and Used EV Subsidies However, there are several factors that differentiate the impacts of new and used EV subsidies. Understanding these differences is critical for assessing the efficiency and distributional consequences of used EV subsidies in contrast to those of new EVs. We identify four primary reasons why real-world effects diverge:

1. 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.

2. Endogenous vehicle scrappage

   The scrap rates of used vehicles depend on vehicle prices, making their supply not perfectly inelastic. Thus, choice of subsidy policies can affect the vehicle stcok composition differently. In the short run, 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.

   Lastly, 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.

3. 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.

4. Vehicle price threshold 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.

Building on these insights, the study will assess the efficiency and equity impacts of used EV subsidies in comparison to new EV subsidies.

Equity Consideration of Used EV Subsidies We will evaluate the impact of transitioning from new to used EV subsidies, incorporating means-testing, and introducing a $25,000 price threshold on increasing benefits to lower-income households. The analysis will examine how these policies individually and collectively enhance the distributional impact of the subsidy. First, we will replace new EV subsidies with used EV subsidies and measure the resulting benefits to lower-income households. Next, we will introduce a buyer income threshold to target subsidies more effectively at low-income buyers. Finally, we will add the $25,000 price threshold to focus benefits on affordable vehicles. At each step, we will assess the incremental increase in benefits to lower-income households. By analyzing the combined effects of these policies, we aim to determine whether their interactions yield additional benefits to low-income households. This approach will offer valuable insights into designing used EV subsidy programs.

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 after 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 Optimal Subsidies

As argued in the text, we assume $\mu = 1$ is the optimal policy. We get two first-order conditions by differentiating W with respect to τ_n and τ_u.

$$\frac{dW}{d\tau_n} = -D_n(p_n - \tau_n - \delta p_u) \cdot [\frac{dp_n}{d\tau_n} - 1 - \delta\frac{dp_u}{d\tau_n}] + D_n(p_n - \tau_n - \delta p_u) \cdot [\frac{dp_n}{d\tau_n} - 1]$$
$$+ \frac{dD_n}{d\tau_n}[p_n - c + \phi - \tau_n] - \delta D_u(p_u - \tau_u)\frac{dp_u}{d\tau_n} + \delta\frac{dD_u}{d\tau_n}[\phi - \tau_u] + \delta\frac{dR}{d\tau_n}[v_s - p_u] - \delta R\frac{dp_u}{d\tau_n} = 0 \quad (29)$$

and

$$\frac{dW}{d\tau_u} = -D_n(p_n - \tau_n - \delta p_u) \cdot [\frac{dp_n}{d\tau_u} - \delta\frac{dp_u}{d\tau_u}] + D_n(p_n - \tau_n - \delta p_u) \cdot \frac{dp_n}{d\tau_u} + \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n)$$
$$- \delta D_u(p_u - \tau_u) \cdot [\frac{dp_u}{d\tau_u} - 1] + \delta\frac{dD_u}{d\tau_u}(\phi - \tau_u) - \delta D_u(p_u - \tau_u) - \delta R(p_u)\frac{dp_u}{d\tau_u} + \delta \cdot (v_s - p_u)\frac{dR}{d\tau_u} = 0 \quad (30)$$

where the arguments on the derivatives of D_n, D_u and R have been suppressed due to the assumed linearity. Simplifying and using the market clearing condition that $D_n(p_n - \tau_n - \delta p_u) = D_u(p_u - \tau_u) + R(p_u)$ gives

$$\frac{dW}{d\tau_n} = \frac{dD_n}{d\tau_n}[p_n - c + \phi - \tau_n] + \delta\frac{dD_u}{d\tau_n}[\phi - \tau_u] + \delta\frac{dR}{d\tau_n}[v_s - p_u] = 0 \quad (31)$$

and

$$\frac{dW}{d\tau_u} = \frac{dD_n}{d\tau_u} \cdot (p_n - c + \phi - \tau_n) + \delta\frac{dD_u}{d\tau_u} \cdot [\phi - \tau_u] + \delta\frac{dR}{d\tau_u}[v_s - p_u] = 0. \quad (32)$$

A final simplification gives

$$\tau_n = p_n - c + \phi + \delta\frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}}[\phi - \tau_u] + \delta\frac{\frac{dR}{d\tau_n}}{\frac{dD_n}{d\tau_n}}[v_s - p_u] \quad (33)$$

and

$$\tau_n = p_n - c + \phi + \delta\frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}}[\phi - \tau_u] + \delta\frac{\frac{dR}{d\tau_u}}{\frac{dD_n}{d\tau_u}}[v_s - p_u]. \quad (34)$$

This gives two equations and two unknowns. Utilizing the values from Proposition 1 we can solve for τ_u and τ_n in terms of the primitives. For reference the intermediate values we require (solving using the results from Proposition 1) are

$$\frac{\frac{dD_u}{d\tau_n}}{\frac{dD_n}{d\tau_n}} = \frac{D'_u[-\mu D'_n]}{D'_n[\theta\mu(D'_u + R') - \mu[(1+\theta)(D'_u + R') + \delta D'_n] + \delta\mu D'_n]} = \frac{D'_u}{D'_u + R'}, \quad (35)$$

$$\frac{\frac{dR}{d\tau_n}}{\frac{dD_n}{d\tau_n}} = \frac{R'[-\mu D_n']}{D_n'[\theta\mu(D_u'+R') - \mu[(1+\theta)(D_u'+R') + \delta D_n'] + \delta\mu D_n']} = \frac{R'}{D_u'+R'}, \tag{36}$$

$$\frac{\frac{dD_u}{d\tau_u}}{\frac{dD_n}{d\tau_u}} = \frac{D_u'[(1+\theta)\mu D_u' - \mu[(1+\theta)(D_u'+R') + \delta D_n']}{D_n'[\theta\delta\mu D_u' - \delta(1+\theta)\mu D_u']} = \frac{(1+\theta)R' + \delta D_n'}{D_n'\delta}, \tag{37}$$

$$\frac{\frac{dR}{d\tau_u}}{\frac{dD_n}{d\tau_u}} = \frac{R'[(1+\theta)\mu D_u']}{D_n'[\theta\delta\mu D_u' - \delta(1+\theta)\mu D_u']} = \frac{R'(1+\theta)}{-\delta D_n'}. \tag{38}$$

τ_u is found by equating equations 33 and 34, simplifying with the previous intermediate results, and solving

$$[\phi - \tau_u] \cdot [\frac{D_u'}{D_u'+R'} - \frac{(1+\theta)R' + \delta D_n'}{D_n'\delta}] = [v_s - p_u] \cdot [\frac{R'(1+\theta)}{-\delta D_n'} - \frac{R'}{D_u'+R'}], \tag{39}$$

yielding

$$\tau_u^* = \phi + [v_s - p_u] \cdot (\frac{R'(1+\theta)[D_u'+R'] + \delta R' D_n'}{\delta D_u' D_n' - (D_u'+R') \cdot [(1+\theta)R' + \delta D_n']}). \tag{40}$$

a final simplification gives

$$\tau_u^* = \phi - [v_s - p_u]. \tag{41}$$

Plugging 41 into 33 yields

$$\tau_n = p_n - c + \phi + \delta[v_s - p_u]\frac{D_u'}{D_u'+R'} + \delta\frac{R'}{D_u'+R'}[v_s - p_u] \tag{42}$$

a last simplification yields

$$\tau_n^* = p_n - c + \phi + \delta[v_s - p_u] \tag{43}$$

A.2 Proof of Proposition 1

A.2.1 Incidence of New Vehicle Subsidy

The sellers' first-order condition is $p_n - c = -\theta\frac{D_n}{D_n'}$. Totally differentiating with respect to τ_n gives

$$(1+\theta)\frac{dp_n}{d\tau_n} = \theta\mu + \delta\theta\frac{dp_u}{d\tau_n}. \tag{44}$$

The equilibrium condition is $D_n(p_n - \mu\tau_n - \delta p_u) = D_u(p_u - \mu\tau_u) + R(v_s - p_u)$. Totally differentiating with respect to τ_n gives

$$\frac{dp_u}{d\tau_n} = \frac{D'_n \frac{dp_n}{d\tau_n} - \mu D'_n}{D'_u + R' + \delta D'_n}. \tag{45}$$

Solving this system of two equations and two unknowns gives the left side of Proposition 1.

A.2.2 Incidence of Used Vehicle Subsidy

Totally differentiating sellers' first-order condition with respect to τ_u gives

$$(1+\theta)\frac{dp_n}{d\tau_u} = \delta\theta\frac{dp_u}{d\tau_u}. \tag{46}$$

Totally differentiating the equilibrium condition with respect to τ_u gives

$$\frac{dp_u}{d\tau_u} = \frac{D'_n \frac{dp_n}{d\tau_u} + \mu D'_u}{D'_u + R' + \delta D'_n}. \tag{47}$$

Solving this system of two equations and two unknowns gives the right side of Proposition 1.

A.3 Proof of Corollary 1

Using the results from Proposition 1 and assuming $R' = 0$,

$$\delta \cdot \frac{d(p_n - \mu\tau_n - \delta p_u)}{d\tau_n} = \frac{-\delta\mu D'_u}{(1+\theta)(D'_u) + \delta D'_n} = \frac{d(p_n - \mu\tau_n - \delta p_u)}{d\tau_u} \tag{48}$$

and

$$\delta \cdot \frac{d(p_u - \mu\tau_u)}{d\tau_n} = \frac{-\delta\mu D'_n}{(1+\theta)(D'_u) + \delta D'_n} = \frac{d(p_u - \mu\tau_u)}{d\tau_u}. \tag{49}$$

This proves Corollary 1.

B Bunching Model Appendix

In this appendix, we show that in a model of car dealership pricing, under certain first order approximations, the change in the amount of price bunching around the \$25,000 Section 25E price cap in 2024 versus 2023 identifies the increase in demand from the dealership transfer option that was introduced in that year.

According to IRS (2024b) guidance, an eligible buyer can elect to transfer the entire tax credit to a registered dealership in exchange for cash or as a down payment or partial payment of the purchase price. The buyer must attest to being income eligible, and must repay the credit if their taxable income exceeds the limits. The sale price for the purpose of the \$25,000 price cap is not affected by the buyer's decision of whether to transfer the credit to a dealer. The credit is non-refundable, so a buyer with insufficient tax liability cannot claim the credit. However, a buyer with insufficient tax liability *can* transfer the credit to a dealership, and the dealership could claim the credit.

B.1 Setup

Define $\gamma \in [0, 1]$ as the decision weight that consumers place on the tax credit relative to the upfront vehicle price. This is a reduced-form parameter intended to capture anything that moderates the effect of the tax credit on demand, including (i) some buyers not having tax liability or being uncertain about whether they will, (ii) time discounting of tax credits that won't be realized until next year's taxes, (iii) uncertainty over whether the tax credit will exist next year, (iv) psychological inattention if the future tax credit is "shrouded" relative to purchase prices, in the spirit of Gabaix and Laibson (2006), Chetty, Looney, and Kroft (2009), and the related literature, and (v) uncertainty over whether the buyer will be income eligible. The dealership credit transfer available starting January 2024 could increase γ by affecting the first four factors.

We model the dealership sales process as follows. The dealership exogenously has a vehicle. Periods are indexed by t; we might think of a period as one day. Each period, one potential buyer arrives. Each period's buyer purchases with probability $D(p)$. The dealership knows $D(p)$, so there is no learning or need for price exploration. If the buyer does not purchase, we move to the next period. At the beginning of each period, the dealership incurs a holding cost χ. This captures factors such as the opportunity cost of the physical space for the vehicle, the vehicle's depreciation, and (more loosely) the lost time value of money from a delayed purchase.

In this model, all consumers are eligible for the credit. Consumers that are not eligible would generate a smooth distribution of prices regardless of the credit eligibility price cap, so they would not affect the below calculations about the amount of bunching.

B.2 Price Bunching

The dealership sets (credit-exclusive) price p to maximize expected profits $\pi(p)$. The dealership's expected profit is the price multiplied by the probability of sale on each day times the holding cost for that number of days:

$$\pi(p) = \left[-\chi + pD(p) + (1 - D(p))(p - \chi)D(p) + (1 - D(p))^2(p - 2\chi)D(p) + ...\right] \tag{50}$$
$$= -\chi + p \cdot D(p) \cdot \sum_{t=0}^{\infty}(1 - D(p))^t - \chi D(p) \cdot \sum_{t=0}^{\infty} t(1 - D(p))^t \tag{51}$$
$$= -\chi + p \cdot D(p) \cdot \frac{1}{(1 - (1 - D(p)))} - \chi \cdot D(p) \cdot \frac{1 - D(p)}{(1 - (1 - D(p)))^2} \tag{52}$$
$$= -\chi + p - \chi\frac{1 - D(p)}{D(p)} \tag{53}$$
$$= p - \frac{\chi}{D(p)}. \tag{54}$$

Intuitively, this equation says that the vehicle will eventually sell for price p, but the dealership subtracts the expected holding costs over the periods until the vehicle sells.

Define τ as the tax credit amount, and $\bar{p}$ as the price cap. Under Section 25E, $\bar{p} = \$25,000$, and $\tau = \$4000$ for vehicles with prices near $\bar{p}$. As defined above, γ is the decision weight on the tax credit. The demand function now a kink at $\bar{p}$:

$$D(p) = \begin{cases} D(p), & p > \bar{p} \\ D(p - \gamma\tau), & p \leq \bar{p}. \end{cases} \tag{55}$$

To solve the dealership's problem, we now insert those two different demand functions into the optimal pricing problem:

$$\pi(p) = \begin{cases} p - \frac{\chi}{D(p)}, & p > \bar{p} \\ p - \frac{\chi}{D(p-\gamma\tau)}, & p \leq \bar{p} \end{cases} \tag{56}$$

Define p^n as the optimal price with demand $D(p)$, and define p^e as the optimal price with demand $D(p - \gamma\tau)$. Define π^n and π^e, respectively, as the corresponding optimized profits. For some vehicles with p^n above but near \$25,000, $\pi^e(\bar{p}) > \pi^n(p^n > \bar{p})$, and thus the dealership will charge $\bar{p}$ instead of p^n. There is a cutoff price p^* at which profits are the same from bunching at \$25,000 versus charging the optimal price above \$25,000: the p^* is such that $\pi^n(p^*) = \pi^e(\bar{p})$. That cutoff price is characterized by

$$\pi^n(p^*) = \pi^e(\bar{p}) \tag{57}$$
$$p^* - \frac{\chi}{D(p^*)} = \bar{p} - \frac{\chi}{D(\bar{p} - \gamma\tau)} \tag{58}$$
$$p^* - \bar{p} = \chi\left[D(p^*)^{-1} - D(\bar{p} - \gamma\tau)^{-1}\right]. \tag{59}$$

To proceed, we make the functional form assumption that $D(p)^{-1}$ is linear. While this may initially feel non-standard, it is analogous to standard first-order approximations to demand. Formally, we assume $D(p)^{-1} = a + bp$, with $b > 0$.[2]

Under this first-order approximation, equation (59) becomes

$$p^* - \bar{p} = \chi \left[a + bp^* - a - b \cdot (\bar{p} - \gamma\tau)\right] \tag{60}$$

$$(p^* - \bar{p})(1 - \chi b) = \chi b \gamma \tau \tag{61}$$

$$p^* - \bar{p} = \frac{\chi b \gamma \tau}{(1 - \chi b)}. \tag{62}$$

B.3 Comparing Bunching

We now show that the change in the amount of bunching in 2023 versus 2024 identifies the change in γ from dealership transfer.

Define γ_1 and γ_0, respectively, as γ with and without dealership transfer. Analogously define p_1^* and p_0^* as corresponding the cutoff prices. Dividing equation (62) in those two cases gives

$$\frac{p_1^* - \bar{p}}{p_0^* - \bar{p}} = \frac{\gamma_1}{\gamma_0}. \tag{63}$$

The structural primitives are $\{a, b, \chi\}$. Assume that the joint distribution of those primitives is such that p^n has an approximately locally uniform distribution. In practice, this means that the distribution of used car sale prices in the region of \$25,000 to (say) \$35,000 is approximately locally uniform. Then if $p^* - \bar{p}$ increases by $X\%$, the amount of transactions that bunch below $\bar{p}$ would also increase by $X\%$. Thus, if B_1 and B_0, respectively, are the share of transactions with equilibrium price of \$25,000 at γ_1 and γ_0, we have

$$\frac{B_1}{B_0} = \frac{p_1^* - \bar{p}}{p_0^* - \bar{p}} = \frac{\gamma_1}{\gamma_0}. \tag{64}$$

Thus, under these assumptions, the ratio of the amount of bunching in 2024 relative to 2023 identifies the ratio of γ in 2024 relative to 2023.

[2] We also assume $b\chi \leq 1$, which guarantees that if $\bar{p} < p < p^*$ and $\pi(p^*) = \pi(\bar{p})$ then $\pi(p) \leq \pi(p^*)$, implying $\pi(\bar{p}) \geq \pi(p)$. This places a condition that the value of the decrease in expected holding time from (p^* to $\bar{p} - \gamma\tau$) relative to (p to $\bar{p} - \gamma\tau$) is not greater than the value of the smaller price loss.

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 appendix B, 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.

The 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 ascertain the average selling price of a given new vehicle make and model between August 2022 and December 2023. We keep observations 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 compute tax liability utilizing IRS statistics of income (SOI) data Table 1.2 for tax year 2021 (IRS 2024a). This data provides for each AGI income bin the total number of tax returns by filing status along with total tax liability and the total returns that are taxed. From this, we are able to calculate an average tax liability among returns that are taxed, for a given AGI. We then merge this to the second choice data by assuming that the reported income by purchasers is their AGI. Our results are in Table A1. Column 2 denotes what share of total purchases of new vehicles costing under $26,000 occurs within an income bin. For a given income bin, column 3 shows the percent of tax returns that are untaxed, while column 4 is the percent of returns with under $4,000 tax liability. Column 5 shows the average tax liability among the returns that are taxed.

D Reduced-Form Evidence Appendix

D.1 Tests of Anticipation Effects Before January 2023 Implementation

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 tax credit has an 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

Table A1: **Tax Liability Statistics**

Income	Share of Total Purchases	Untaxed	<4k Tax Liability	Average Tax
$1-20,000	5.98%	87.65%	100%	$0
$20,000-25,000	4.4%	49.04%	100%	$896.44
$25,000-30,000	5.8%	41.37%	100%	$1327.03
$30,000-40,000	12.46%	32.13%	100%	$1970.74
$40,000-50,000	10.06%	20.37%	100%	$2836.5
$50,000-75,000	24.34%	11.36%	47.68%	$4641.24
$75,000-100,000	13.15%	5.17%	5.17%	$7599.15
$100,000-200,000	19.28%	1.51%	1.51%	$15421.73
$200,000-500,000	4.02%	0.22%	0.22%	$49122.69
$500,000-1,000,000	0.27%	0.1%	0.1%	$156324.4
$1,000,000+	0.25%	0.09%	0.09%	$998299.98
Total	100%	19.59%	51.28%	$10685.81

through licensed dealerships.

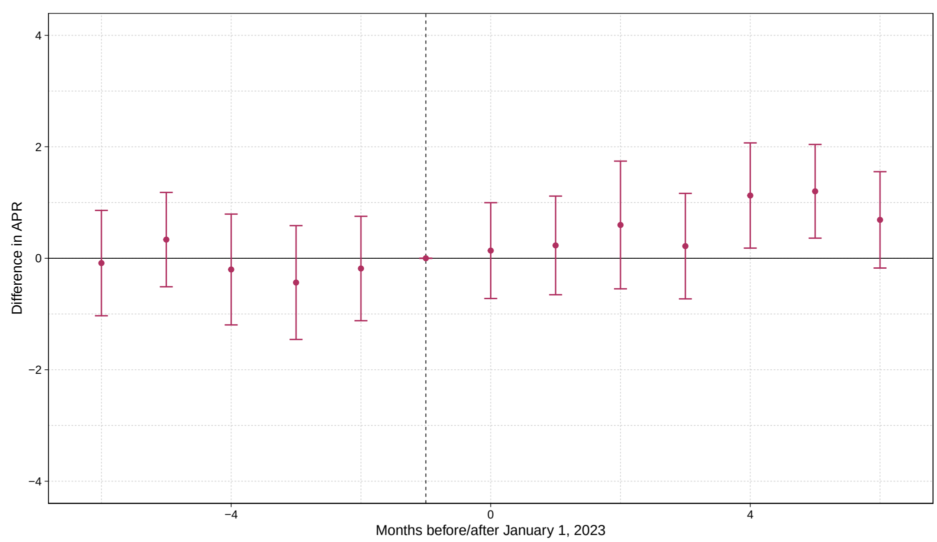
These characteristics of the used vehicle market are important in interpreting the results of the price event studies in Section 5. In order to understand the price response to the tax credit, we need to compare the same type of transactions both with and without the tax credit. If the financing terms 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.1.1 Financing Terms

In this section, we present results for the annual percentage rate (APR) of the loans. Figure A1 shows the results of our triple-difference specification from Section 5.1 with APR as the outcome variable and standard errors clustered at the model by model year level. We do see a statistically significant positive effect in period 4 and 5, but not during the first 4 months after the policy implementation. Given the effect from the corresponding triple-differences estimation shown in Table A1, we reject APR increases of more than 0.862 percent with 95 percent confidence. As comparison, the mean APR in the treatment group of cheap EVs is 13.15 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 immediately respond to the policy change.

Figure A1: **APR Triple-Differences Event Study**

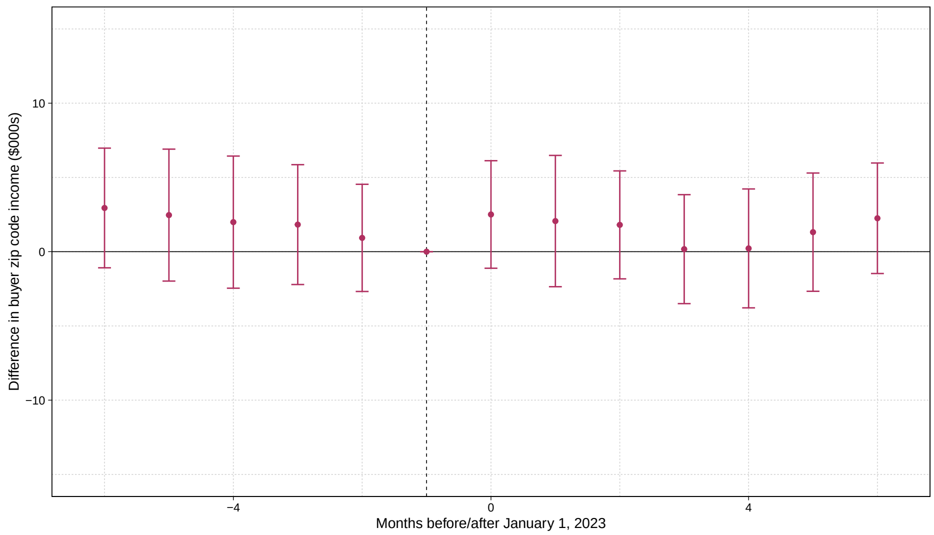


D.1.2 Buyer Income

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 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 A2 shows the results from our triple-difference specification from Section 5.1 with median household income in the buyer zip code as the outcome variable and standard errors clustered at the model by model year 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 A1, we reject a difference in average buyer income from before versus after the policy of more than $1,007 with 95 percent confidence. This lends further evidence that the pre and post-periods consist of comparable transactions.

Figure A2: **Buyer zip code income triple-differences event study**



D.1.3 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 model year. 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 model years 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:

$$\begin{aligned} q_{kyt} = EV_k + G_{ky} + (EV_k \times G_{ky}) + \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^1 G_{ky} \mathbb{1}\{s+t=\tilde{T}\} + \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^2 EV_k \mathbb{1}\{s+t=\tilde{T}\} \\ + \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^3 G_{ky} EV_k \mathbb{1}\{s+t=\tilde{T}\} + (\lambda^{make_k} \times \lambda^t) + \lambda^k + \lambda^y + \epsilon_{kyt} \end{aligned} \tag{65}$$

where q_{kt} monthly transaction quantity for vehicle model k and model year y divided by the average monthly transactions from 2022 and G_{ky} 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 A3 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 A3: **Quantity Triple-Differences Event Study**

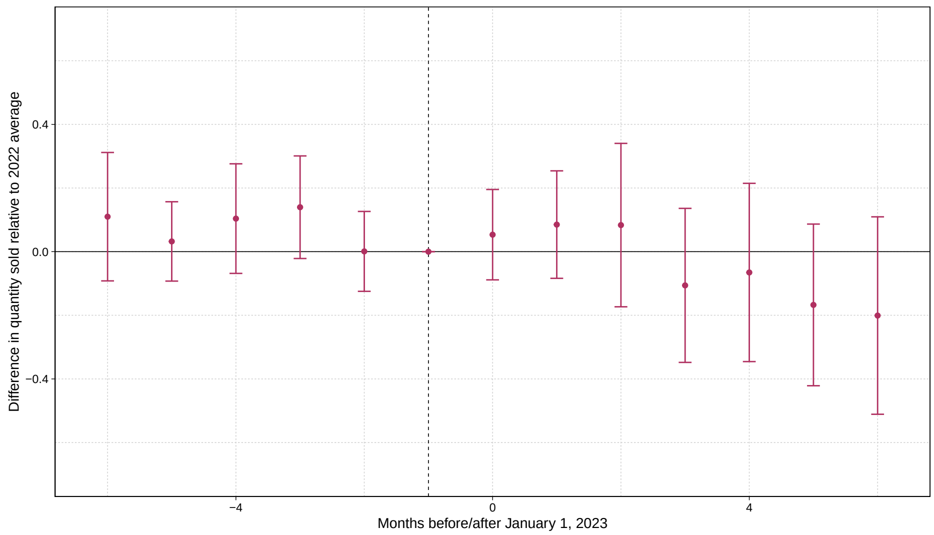


Figure A4 shows the raw total transactions for each treatment group. The y-axis on the left shows the quantity for EVs, and the y-axis on the right is shifted down to show the quantity for GV. As discussed above, we can see that the quantity for expensive EVs is increasing over time, with a jump at the 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 A4: **Raw Transaction Quantity by Treatment Group**

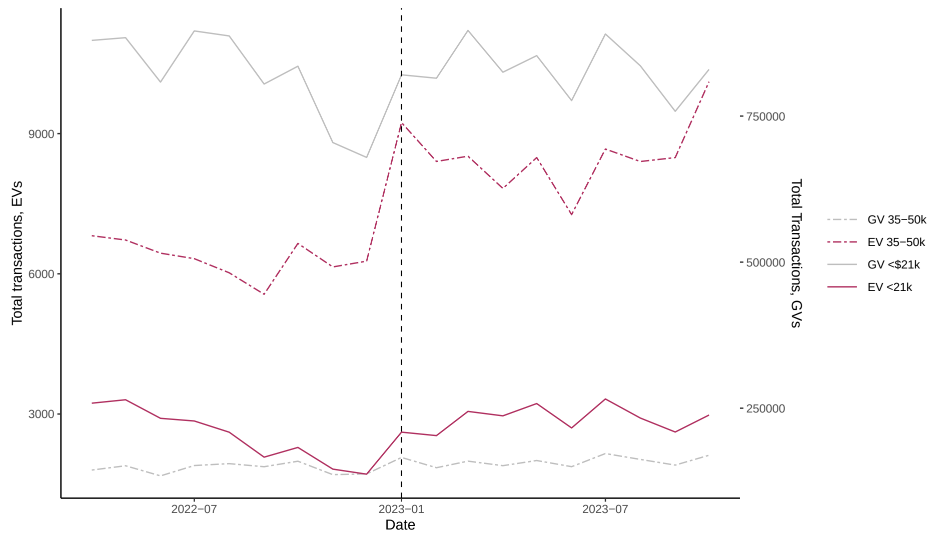
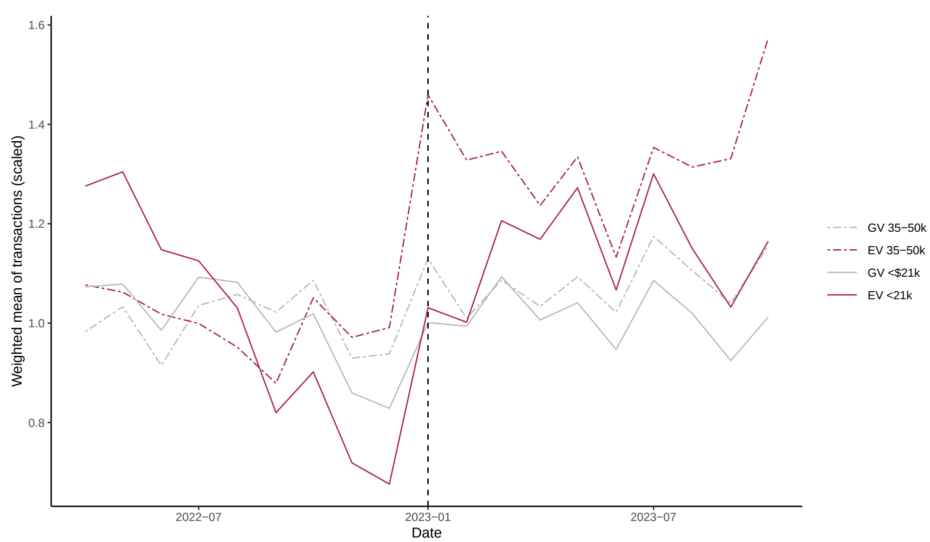


Figure A5 shows the average scaled transaction quantity for each group. While the average scaled transaction quantity for cheap EVs is lower in December 2022 than in January 2023, it is following a pre-existing trend for this group. As we see in the raw totals above, this decrease is occurring for cheap GVs as well.

Figure A5: **Average Scaled Transaction Quantity by Treatment Group**

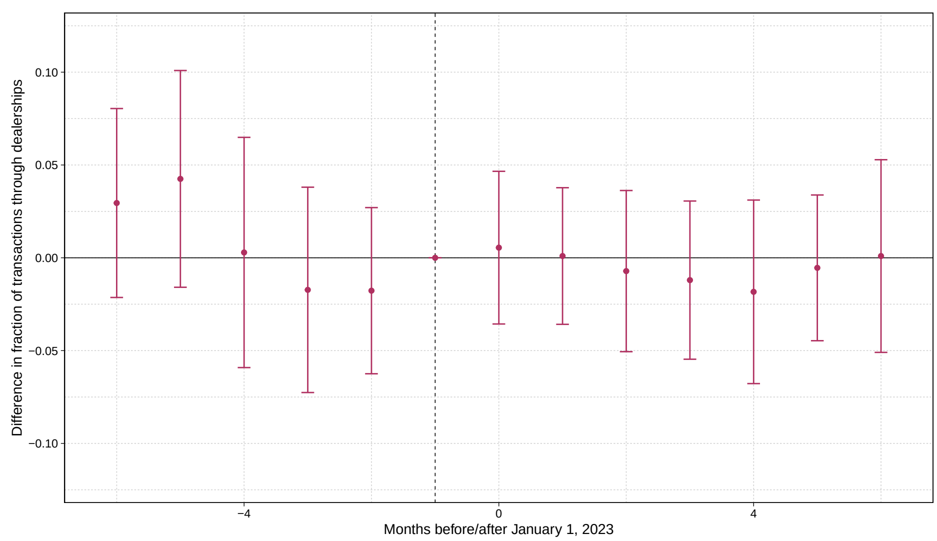


D.1.4 Changes in Dealership Transaction Shares

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 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.1.3, we focus on this second explanation.

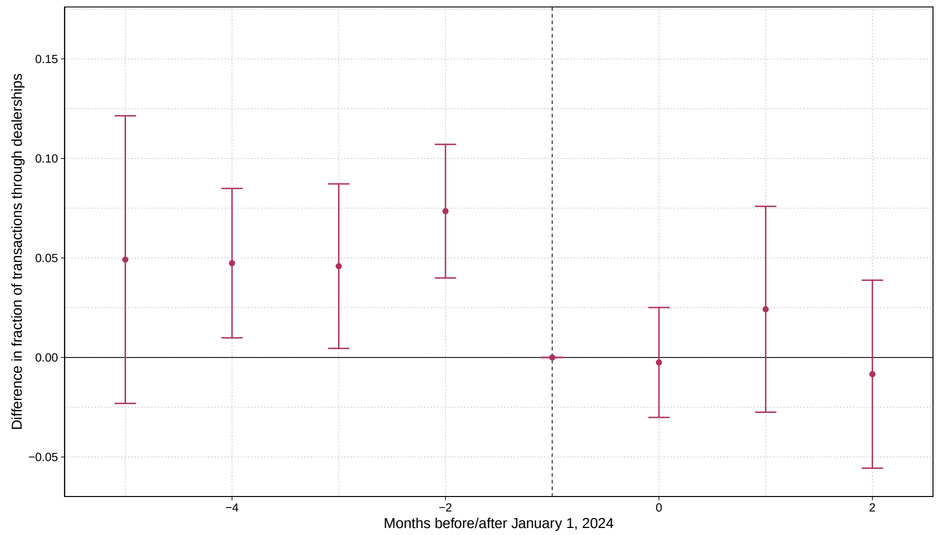
We apply the empirical strategy from Section D.1.3 with dealership share of transactions as the outcome variable. Figure A6 shows the results of this triple-difference event study specification around the 2023 policy event. We do not see evidence that the dealership share of transactions responded to 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.

Figure A6: **Dealership Share Triple-Differences Event Study Around January 2023**



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 A7, 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 current end date of the Experian data.

Figure A7: **Dealership Share Triple-Differences Event Study Around January 2024**



D.2 Event Study Regression Tables

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

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

Model:	(1)	(2)	(3)
Dependent Variable:	log(Transaction price)	APR	Buyer income
Variables			
EV × Predicted price <$21k × After Jan. 2023	-0.0148	0.6446	-0.1044
	(0.0357)	(0.2261)	(0.9400)
Odometer reading	-4.06×10^{-6}	2.32×10^{-5}	-2.03×10^{-5}
	(6.33×10^{-8})	(5.5×10^{-7})	(8.37×10^{-7})
Fixed-effects			
Make × Time-to-treat	Yes	Yes	Yes
Model year	Yes	Yes	Yes
Model	Yes	Yes	Yes
Dealership	Yes	Yes	Yes
Fit statistics			
R^2	0.89769	0.42003	0.32322
Observations	2,055,208	1,047,157	1,983,788

Clustered (model × model year) standard-errors in parentheses

Table A3: **Quantity Effects around January 2023**

Model:	(1)	(2)
Dependent Variable:	Scaled transaction quantity	Dealership %
Variables		
EV × Predicted price <\$21k × After Jan. 2023	−0.2354	−0.0248
	(0.1336)	(0.0135)
Fixed-effects		
Make × Time-to-treat	Yes	Yes
Model year	Yes	Yes
Model	Yes	Yes
Fit statistics		
R^2	0.41214	0.96694
Observations	30,742	29,643

Clustered (model × model year) standard-errors in parentheses

D.3 Measuring Excess Bunching

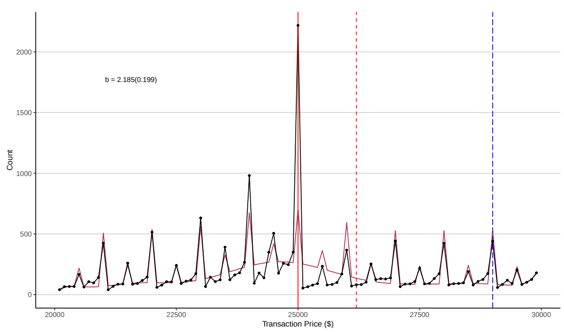
The goal of this section is to quantify the excess mass in the transaction price distribution under \$25,000 shown in the descriptive analysis in Section 5.2. Comparing excess mass across 2023 and 2024 can help us identify the extent to which the dealership credit transfer increased the value of credits to consumers.

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.

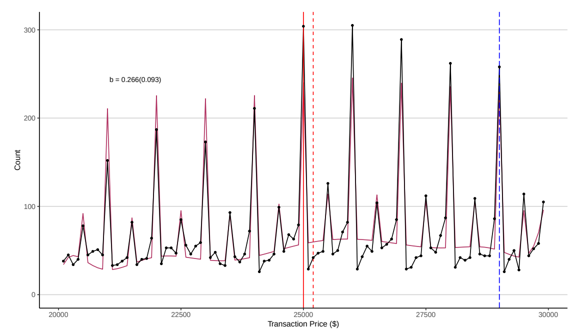
Figure A8 shows an example of this analysis for the transaction price distribution of EVs in 2022 and 2024. The black line shows the values from the data and the solid red line shows the counterfactual distribution constructed as described above. The red dotted lines show the upper bound of the missing 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 A8: **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 A9 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 A9: **Excess Mass by Month**