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

Hunt Allcott   Hyuk-soo Kwon   Tess Snyder*

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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.

*Allcott: Stanford University and NBER. allcott@stanford.edu. Kwon: University of Chicago. hskwon@uchicago.edu. Snyder: Stanford University. tsnyder2@stanford.edu. We thank seminar participants at Berkeley Energy Camp for helpful comments. We are grateful to Jonathan Smoke, Erin Keating, and the team at Cox Automotive for sharing vehicle transaction data, and to Chris Chaney at Strategic Vision for sharing second choice survey data. We are grateful to Levi Kiefer for exceptional research assistance.

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: the primary way that used EV transaction credits might increase the stock of EVs on the road is through increasing used EV prices, but this 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 XX and YY percent of new and used vehicle transactions at dealerships from 2021–2024. We add data on vehicle characteristics, the nationwide 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 three reduced-form analyses, each of which identifies a key model parameter. First, we estimate effects on used EV transactions prices after the IRA unexpectedly passed in August 2022 but before the used EV transaction credit took effect in January 2023. This is a unique natural experiment that increased EVs' resale values without otherwise affecting their value to the current buyer. This provides a unique opportunity to measure the extent to which vehicle buyers pay attention to resale values. We estimate that used EV prices did not increase significantly relative to used gasoline vehicle (GV) prices, and our 95 percent confidence intervals rule out effects of more than about $XX for the average sale. This implies either that buyers did not expect any effect on used EV prices, or that they were inattentive to those effects in the short run after the IRA passed.

Second, 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 $XX. 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.

Third, 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 or increased certainty or salience.

To better understand market dynamics and potential long-term effects, we developed 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; Jacobsen and van BenThem, 2015; 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; 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; 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 2–11, 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. This dealership transfer

The IRA's passage was a surprise given public information before late July 2022 (Bauer et al., 2023). A tax credit for used EVs was first proposed as part of the Build Back Better Act passed in the House of Representatives in 2021. In December 2021, Senator Joe Manchin announced that he would not support this legislation, meaning that it would not get enough votes to pass in the Senate. On July 14, 2022, press reports came out reiterating Manchin's stance against the Build Back Better Act and claiming that he would not support any other climate legislation. On July 27, 2022, however, Senator Manchin and Senate Majority Leader Charles Schumer unexpectedly announced their agreement on the IRA, along with the complete text, signaling that this was very likely to pass the Senate and be enacted into law. Indeed, the IRA passed the Senate and House on August 7 and 12, respectively, and President Biden signed it into law on August 16, 2022. Thus, on July 27th, the publicly perceived probability of used EV tax credits increased substantially, likely from near zero to near 100 percent.

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 (electric vehicles) with less negative consumption externalities than its alternative (gasoline vehicles). 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 resold at price p_u to either individual used vehicle buyers or scrappers.

Define ϕ as the negative externality reduction (or equivalently, positive externality) from consuming EVs relative to the alternative (gasoline vehicles). 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 $D_n := D_n(p_n - \mu\tau_n - \delta p_u)$, and used vehicle demand is $D_u := D_u(p_u - \mu\tau_u)$, with $D'_n \leq 0$ and $D'_u \leq 0$.

Scrappage demand is $R := R(p_u)$, with $R' \leq 0$. We assume that scrappers generate zero net profits.

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 $S := S(p_n)$.

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, producer surplus, and positive externalities net of government spending:

$$W(\tau_n, \tau_u) = \underbrace{\int_{p_n-\tau_n-\delta p_u}^{\infty} D_n(x)dx + D_n \cdot (p_n - c + \phi - \tau_n)}_{\text{New EV CS, PS, externality, and subsidy}} + \delta \underbrace{\int_{p_u-\tau_u}^{\infty} D_u(x)dx + D_u \cdot (\phi - \tau_u)}_{\text{Used EV CS, externality, and subsidy}} \quad (1)$$

3.2 Optimal Policy

Given this standard partial equilibrium setup, the total surplus-maximizing policy is a straightforward Pigouvian subsidy: subsidize new EVs by the positive externality plus the markup, and subsidize used EVs by the positive externality.

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

$$\begin{aligned} \tau_n^* &= p_n - c + \phi \\ \tau_u^* &= \phi. \end{aligned} \quad (2)$$

Proof: see Appendix A.1.

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 new vehicle buyers don't discount resale prices and scrappage is fully inelastic, the two types of subsidies have the same effects on equilibrium prices:

Corollary 1 (Symmetry): If $\delta = 1$ and $R' = 0$, then new and used EV subsidies have the same effects on equilibrium subsidy-inclusive prices:

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

Proof: see Appendix A.3.

The intuition for this corollary is as follows. If new EV buyers do discount resale prices ($\delta < 1$), then this mutes the effects of used EV subsidies on new vehicle prices. If scrappage is elastic ($R' < 0$), then some of the subsidies are dissipated through the change in scrappage. However, with no discounting and inelastic scrappage, the new versus used EV subsidies are subsidizing the supply versus demand of the used EV market. Just as in the textbook case of subsidizing supply versus demand, statutory incidence is independent of economic incidence.

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.

One key simplification is that we have not yet modeled the possibility of multiple transactions for each used vehicle. This would increase the possibility that a vehicle is eventually sold to an eligible buyer, muting the effects of eligibility restrictions.

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 micro-data covering July 2021 to May 2024 from Cox Automotive, including both new and used transactions. These data cover about XX and YY percent of new and used transactions, respectively through dealerships in 2022 and 2023. 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 vehicles 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.

One additional aspect of the data that we utilize for just the structural model is aggregating to the car type level (rather than model name). Car type involves two parts: a car segment part which is either car, SUV, pickup, or van, as well as a size component such as compact, midsize, or large. An example observation is "SUV - midsize." We explicitly exclude sports cars due to their overall small transaction share and their arguably composing a separate market with different vehicle characteristics driving demand. We impose a single car type for each model across all model years to increase the cohesion of the vehicle stock across model years. The motivation for using car type originates from the practice of manufacturers changing vehicle models relatively frequently, leading to sharp discontinuities in vehicle stocks at the level of make, model, model year. We also try to 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 three key parameters characterizing important aspects of resale markets and tax credit policy: attention to resale prices, tax credit pass-through, and the value of dealership transfer.

5.1 Summer 2022 Event: Attention to Resale Prices

Due to the surprise proposal of the IRA on July 27, 2022 and passage of the IRA on August 16, 2022, there was an unexpected increase in the resale value of EVs. It would be reasonable to expect this tax credit to have some incidence on the sellers, meaning that future resale prices may be higher. If current buyers are attentive to future resale values, we would expect to see the increase in resale value reflected in prices. This section presents an event study comparing prices of EVs and GVs before and after the announcement of the IRA.

5.1.1 Empirical Strategy

We estimate the effects of the announcement of the Used Clean Vehicle Credit on transaction prices using a difference-in-differences design. The dependent variable, $\ln(p_{ikyt})$, is defined as the price of transaction i of vehicle model k and model year y in period t. The pre-period starts on the week of March 21, 2022 up to July 24, 2022. The post-period begins on July 25, 2022 and extends to the week of November 5, 2022. We define EV_i as the treatment indicator for whether the transacted vehicle is an EV, λ^t as the period fixed effect, λ^k as a model fixed effect, λ^y as a model year fixed effect, λ^{d_i} as a dealership fixed effect, and odo_{ikyt} as the odometer reading of the vehicle in the transaction. The estimating equation is

$$\ln(p_{ikyt}) = \gamma EV_k \times \lambda^t + EV_k + \lambda^t + \lambda^k + \lambda^y + \lambda^{d_i} + odo_{ikyt} + \epsilon_{ikyt}. \tag{6}$$

We cluster standard errors at the model by model year level. We also estimate an event study with separate fixed effects and γ coefficients for each bi-weekly period from $T_{pre} = 2022/06/13$ to $T_{post} = 2022/09/05$.

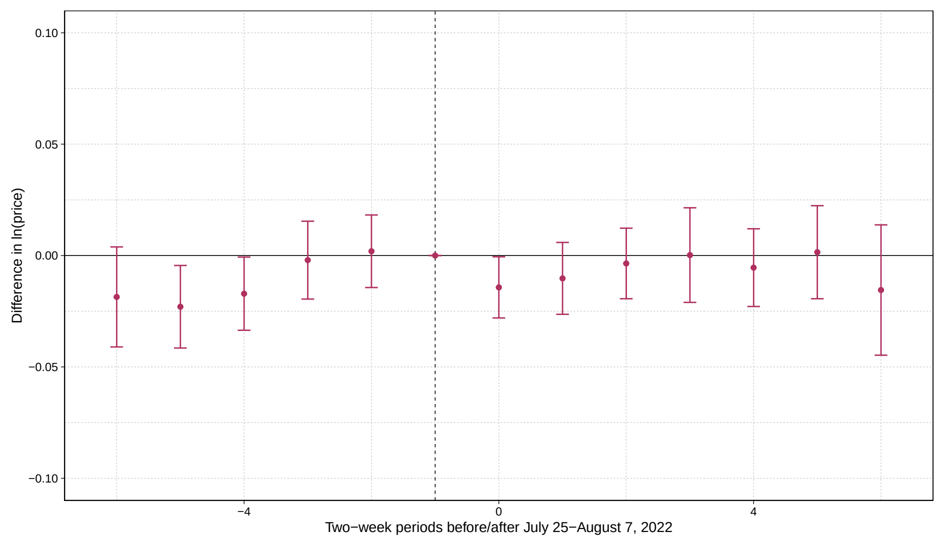
The sample includes all used vehicle transactions from the Cox data as described in Section 4. We exclude new vehicles because their prices typically respond less to market shocks due to their more elastic supply (Busse, Knittel, and Zettelmeyer 2013).

Recall that we observe the transaction week, but not the day. We thus define the treatment period as the week beginning July 25, 2022, to ensure that the pre-period does not include any days after the IRA announcement. Period 0 contains the dates when the IRA was announced and passed in the Senate, during which the likelihood of being passed into law became very high. Period 1 contains the date on which the IRA was officially passed into law.

5.1.2 Results

Figure 1 shows the results for the event study around the IRA announcement. Relative to the $t = -1$ baseline period, there is no statistically significant increase in used EV prices in any two-week period through September 5, 2022.

Figure 1: **Price Effect of IRA Announcement on Used EVs**



There are two potential explanations for these results. First, used EV buyers might be inattentive to the increase in EV resale values caused by the IRA. Second, consumers may be attentive to future resale prices but assume that the price effects of the tax credit will be limited. Our estimates in the next two subsections speak to these two different explanations.

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. Limiting to short-run estimates and using gasoline vehicles as a control group makes our event study estimates more credible. Second, we show only the short run response to this policy announcement, and consumer expectations and responses may differ in the long run. Third, used GVs, the control group, are affected by changes in the used EV market in equilibrium. We will use a structural model to understand the full equilibrium effects.

5.2 January 2023 Event: Tax Credit Price Effect

The implementation of the tax credit occurred about five months later 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.

5.2.1 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 estimate the following regression equation using data from the pre-period:

$$\ln(p_{ikyt}) = \lambda^{ky} + \lambda^{m_t} + \lambda^{d_i} + \beta \cdot odo_{ikyt} + \sum_{s=2011}^{2021} \gamma_s \mathbb{1}\{y = s\} \cdot P_t + \epsilon_{ikyt} \tag{7}$$

where p_{ikyt} is the price of transaction i of vehicle model k and model year y in bi-weekly period t, $\lambda^k \times \lambda^y$ is a vehicle model by model year fixed effect, λ^{m_t} is a month-of-year fixed effect, λ^{d_i} is a dealership fixed effect, 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 (July 2021).

Here, time periods are defined as months. 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 the age of the model. 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 starts on the week of August 29, 2022 up to December 21, 2022. The post-period begins on January 1, 2023 and extends to the week of May 1, 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 $25,000 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 bi-weekly period t.

$$\begin{aligned}\ln(p_{ikyt}) = & EV_k + G_i + EV_k \times G_i + G_i \times \lambda^t + EV_k \times \lambda^t \\ & + G_i \times EV_k \times \lambda^t + (\lambda^{make_k} \times \lambda^t) + odo_{ikyt} + \lambda^k + \lambda^y + \lambda^{d_i} + \epsilon_{ikyt}\end{aligned} \tag{8}$$

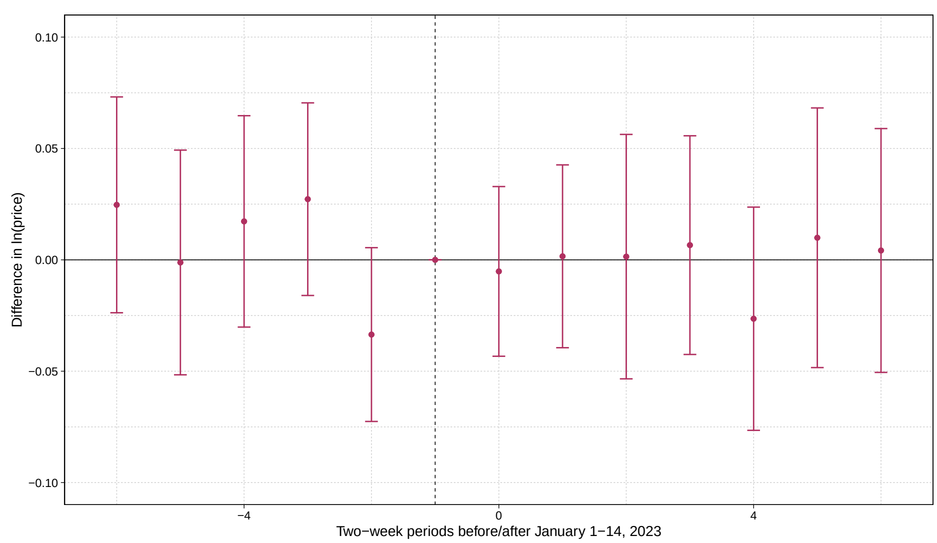
We include the interaction between vehicle make and time period to account for trends across manufacturers. We cluster standard errors at the model by model year level.

5.2.2 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.

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



The same caveats discussed in Section 5.1 apply to this analysis. In addition, 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 theoretically affect our estimates. In reality, however, Appendix B.1 shows that there is no evidence of such anticipation effects.

5.3 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 3 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 3: **Sale Price Distribution for Used Vehicles**

(a) EVs (b) GVs

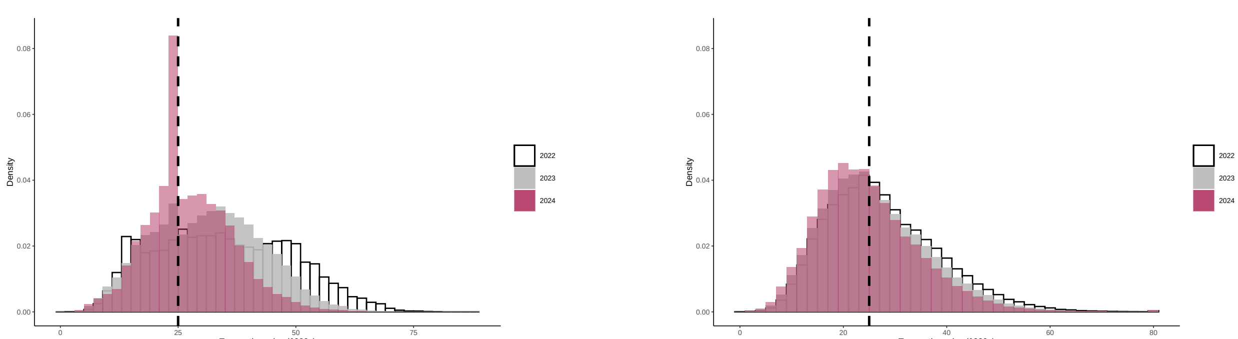
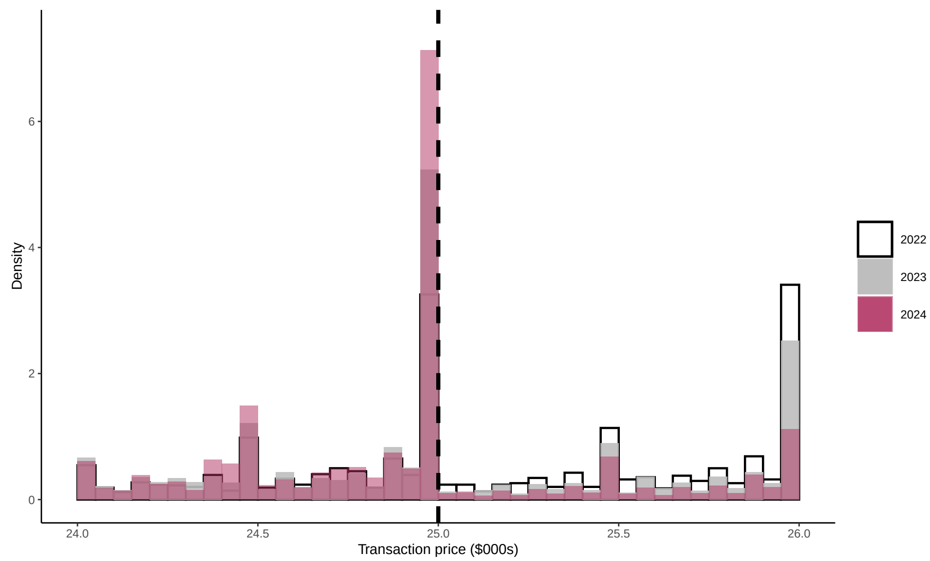


Figure 4 shows the portion of the price distribution just above and below $25,000. We can see that bunching generally occurs at round numbers, and the density right at $25,000 in 2024 exceeds the 2023 value. We see additional excess mass around and below \$24,500 in 2024 compared to both 2022 and 2023.

Figure 4: **Used EV Sale Price Distribution Around \$25,000**



Appendix (TBD) 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 B.2 estimates that bunching increased by several multiples by mid-2024 relative to 2023, which implies that dealership transfer had large effects on demand.

Appendix B.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 and holding time h_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

$$U_{ijat} = \sum_{k=0}^{h_i-1} \rho^k \widetilde{u}_{ija+k} + P_{ijat} - \rho^{h_i} P_{ija+h_i,t+h_i} \tag{9}$$

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

$$u_{i0} = 0. \tag{11}$$

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

$$g_{ja}(p) = \zeta_{ja} \cdot (p)^{\eta_p} \tag{12}$$

where η_p represents the price elasticity of the scrap probability.

6.3 Consumer Expectation on Future Prices

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: $p_{ja+h_i,t+h_i} = p_{ja+h_i,t}$. In the second case, consumers form expectations about the depreciation rate for vehicle j: $p_{ja+h_i,t+h_i} = (d_j)^{h_i} \cdot p_{jat}$, where d_j is the expected depreciation rate, which is endogenous in the model.

6.4 Expected Rent

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

$$P_{ijat} = \alpha_i p_{jat} \tag{13}$$

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:

$$P_{ija+h_i,t+h_i} = -\alpha_i r_{ijat} \tag{14}$$

where r_{ijat} is the resale or scrap value of vehicle j of age a after consumer i's holding period. If consumers are myopic, the expected future value becomes:

$$r_{ijat} = \Big[1 - g_{ja+h_i}(p_{ja+h_i,t})\Big]\, p_{ja+h_i,t} + g_{ja+h_i}(p_{ja+h_i,t})\, \underline{p}_j \tag{15}$$

where $\underline{p}_j$ is the scrap value of model j. On the other hand, if consumers form expectations about the depreciation rates,

$$r_{ijat} = \Big[1 - g_{ja+h_i}((d_j)^{h_i} p_{jat})\Big]\, (d_j)^{h_i} p_{jat} + g_{ja+h_i}((d_j)^{h_i} p_{jat})\, \underline{p}_j \tag{16}$$

Equations (15) and (16) allow us to suppress the time subscript t since the expected future value depends only on the current prices. We can now rescale Equation (10) to define the per-period individual utility as

$$\begin{aligned} u_{ija} &= \widetilde{u}_{ija} + \beta_i^a \Big(1 - \tfrac{1}{\sum_{k=0}^{h_i-1} \rho^k}\Big) + \alpha_i \tfrac{p_{ja} - r_{ija}}{\sum_{k=0}^{h_i-1} \rho^k} &(17)\\ &= \widetilde{u}_{ija} + \beta_i^a A_{ija} + \alpha_i B_{ija} &(18)\end{aligned}$$

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

$$u_{ija} = X_{ja}\beta_i + \xi_{ja} + \beta_i^a (a + A_{ija}) + \alpha_i B_{ija} + \varepsilon_{ija} \tag{19}$$

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:

$$\pi_{ft} = \max_{\{p_{jat}|a=0,\ j\in J_{ft}\}} \sum_{j\in J_{ft}} (p_{j0t} - mc_j)\, Q(\boldsymbol{p}_{a=0,t},\ \boldsymbol{p}_{a>0,t},\ \boldsymbol{q}_{a>0,t}) \tag{20}$$

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 three groups of consumers:

R1) **New vehicle buyers**

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 $\Omega^j_{1,6}$. If we adopt fixed selling points instead of holding time, consumers with a selling point at age 6 will correspond to $\Omega^j_{1,6}$.

R2) **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

R3) **Used vehicle buyers**

The values in the first column of the previous COM (multiplied by one minus scrap probabilities) are now divided and allocated into the red-shaded area in the new COM. For example, the number of consumers of product j aged a whose holding time is t years or whose fixed selling point is $a+t-1$ will be added to $\Omega_{a,t}$ of 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:

$$\text{\# of consumers with holding period of 1 year : 2 years : } \ldots \text{ : T years} = c_1 : 2 \cdot c_2 : \ldots : T \cdot c_T \tag{21}$$

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

$$y_{jat} = \frac{N_{jat} - N_{ja+1,t+1}}{N_{jat}} \tag{22}$$

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,

$$g_{jat} n_{jat} = N_{jat} - N_{ja+1,t+1} = y_{jat} N_{jat} \tag{23}$$

where $N_{jat} - N_{ja+1,t+1}$ is the number of scrapped vehicles. Since we observe all the values in Equation (23) 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:

$$g_{jat} = exp(\zeta_j + \eta_a a_j + \epsilon_{jat}) \cdot (p_{ja})^{\eta_p} \tag{24}$$
$$\Rightarrow \; ln(g_{jat}) = \zeta_j + \eta_a a_j + \eta_p ln(p_{ja}) + \epsilon_{jat}$$

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

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

OLS estimates of the scrap parameters. The price elasticity of scrap rates is similar to that found in Jacobsen and van BenThem (2015), where the scrap elasticity is estimated at -0.7.[1] However, there could be an endogeneity issue as the price p_{jat} might be correlated with the scrappage shock ϵ_{jat}. Thus, we calibrate $\eta_p = -0.7$ 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.

[1] Jacobsen and van BenThem (2015) use the yearly scrap rates y_{jat} instead of the scrap rates after holding periods. However, Equation (23) shows that the price elasticity of scrap rates is identical for both cases

$$\frac{dln(y_{jat})}{dln(p_{jat})} = \frac{dln(g_{jat})}{dln(p_{jat})} = \eta_p \tag{25}$$

7.3 Depreciation Rates

For the case where consumers are not myopic, we need to compute the expected depreciation rate d_j to construct the per-period rents of vehicle ownership. We calculate it as the average percent change in price between each model year within a vehicle category.

$$d_j = \frac{\sum_{a=\min a_j+1}^{\max a_j} (p_{j,a-1} - p_{j,a})/p_{j,a-1}}{\max a_j - \min a_j} \tag{26}$$

where a_j is the set of observed ages for vehicle type j. Given that consumer expectations over price depreciation are set by the price distribution in each period, the number of depreciation rates to calculate adds complexity to the equilibrium simulations for the counterfactual analysis. Because of this, we aggregate the depreciation rates to the fuel-type level. This gives us two depreciation rates in each period-one for EVs and one for GVs-that are calculated as follows:

$$d_F = \frac{\sum_{j\in\mathcal{J}_F} \sum_{a=\min a_j+1}^{\max a_j} (p_{j,a-1} - p_{j,a})/p_{j,a-1}}{\sum_{j\in\mathcal{J}_F} 1} \tag{27}$$

where $F \in EV, GV$ represents the fuel types, $\mathcal{J}_F$ is the set of vehicles with $F_j = F$, $\min a_j$ is the youngest age at which we observe vehicle j, and $\max a_j$ is the oldest age at which we observe vehicle j. The values of $\min a_j$ and $\max a_j$ may differ across vehicle types based on when that vehicle type was introduced to the market or discontinued.

7.4 Demand Parameters

From our utility specification in Equation 19, we need to estimate $(\alpha, \beta_0, \beta_a, \lambda_j)$ in the following equation:

$$u_{ija} = \beta_0 + \lambda_j + \beta_a(a + A_{ija}) + \frac{\alpha}{inc_i} B_{ija} + \varepsilon_{ija} = \delta_j + \beta_2^a h_i(a_j + A_{ija}) + \frac{\alpha}{inc_i} B_{ija} + \varepsilon_{ija} \tag{28}$$

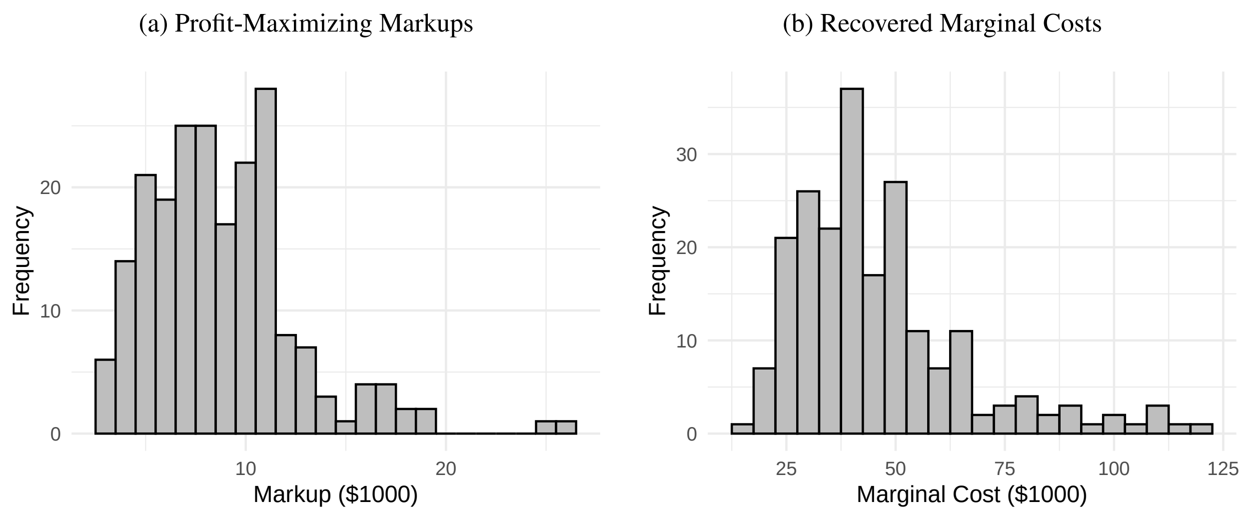
where λ_j represents the model fixed effect, and inc_i is the simulated income of consumer i. Given that price sensitivity is defined as $\alpha_i = \alpha/inc_i$, wealthier consumers are less price sensitive than those with lower incomes. We set $\rho = 0.97$ to calculate the age adjustment factor A_{ija}, and use depreciation rates and scrappage parameters to compute the average rent B_{ija}. We estimate α by matching the average model-implied price elasticity across new vehicle types to -5.06, the average price elasticity found in Grieco et al. (2023). We follow Berry et al. (1995) to recover the mean utilities δ_{ja} by matching the observed and model-predicted market shares of vehicles. 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)	-44.45
	(-)
Constant (β_0)	-2.465
	(0.494)
Age (β_a)	-0.112
	(0.005)
Model FE	Yes
Observations	3,374

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

Figure 5: **Markups and Marginal Costs of New Car Production**



7.5 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 Policy Evaluation

8.1 Used EV Tax Credit

There are several features of this policy that add complexity to the equilibrium analysis. First, we now need to categorize the same EV model into two types: products that have never used EV credits and those that have been traded to eligible consumers and have no remaining credits. An EV with an available credit has a higher value than the same EV (same age and same model). We refer to the price gap between the same EVs due to the presence of used EV credits as a credit premium.

A credit premium is positive but cannot exceed the value of used EV credit, which is \$4k. 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 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 affluent 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 with available credits in the market, then premiums become lower, while if there are many used EVs without remaining credits, then premiums become higher.

Second, the one-time nature of the used EV credits makes the vehicle market non-stationary. Let Ω^j represent the COM for EV model j that has not used the credit yet, while $\widetilde{\Omega}^j$ counts the number of product j that has used the credit before.

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

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. Note that first two rows of $\widetilde{\Omega}^j$ cannot contain non-zero elements because the used EV credits are only eligible for EVs older than 2 years.

Lastly, we need to divide used EV transactions into four types depending on whether the EVs have remaining used EV credits and whether the transactions are eligible for the used EV credits. These four different types of transactions generate different anticipated rents for consumers, different individual utilities, and different price elasticities. Moreover, when we update the market structure (product-specific COMs), we need to track these four types of transactions differently.

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

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) and consumers' expectations on price depreciation and premium appreciation rates need to be rational,[2] we need to establish a nested simulation structure with four levels. Throughout the simulation years, there are average depreciation and appreciation rates of vehicle prices and credit premiums. Given the average rates as consumers' beliefs, we build each year's equilibrium, which consists of three layers of loops. In the innermost loop, we search for the used car prices, given the new car prices and credit premiums that clear the used car market. In the middle loop, we search for the credit premiums that adjust the demand ratio for EVs with and without credits for each model. Lastly, in the outer loop, we search for the new car prices that maximize firm profits, given the credit premiums.

The following details the simulation steps:

[2] Even with partial foresight, it can still be considered perfect foresight if their beliefs are accurate. Simulating perfect foresight can be conceptually challenging because, for example, to simulate the 2023 equilibrium, we would need to know the equilibrium prices for 2027. To simulate the 2027 equilibrium, we would require the 2031 equilibrium, and so on. If we had a "final" period with known equilibrium outcomes, we could simulate backward from that final period. However, it's unclear when this final period should be and what it should look like.

1. Start with consumers' expectations on a price depreciation rate d_j, a premium appreciation b_j, car prices p_{jat}, and credit premiums l_{jat}. Here, the subscript t represents a simulation year, such as 2023, 2024, and so on.

2. For simulation year t, given new car prices p_{j0t} and credit premiums l_{jat}, search for the used car prices p_{jat} for $a > 0$ such that

$$D_{jat}(p_{jat}, l_{jat}) + \widetilde{D}_{jat}(p_{jat}, l_{jat}) = \Omega_{a1}^{jt} + \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a > 0 \tag{29}$$

   where D is the demand for vehicles with the credit option, and $\widetilde{D}$ is the demand for EVs without the available credits remaining.

3. Confirm whether the credit premiums used in Step 2 satisfy the following conditions

$$D_{jat}(p_{jat}, l_{jat}) : \widetilde{D}_{jat}(p_{jat}, l_{jat}) = \Omega_{a1}^{jt} : \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a \tag{30}$$

   Otherwise, update the credit premiums and return to Step 2.

4. Verify whether the new car prices used in Step 2 satisfy the first-order conditions of firms' profit maximization. If not, update new car prices and return to Step 2.

5. Repeat Steps 2-4 until prices and premiums in the simulation year t satisfy firms' profit maximization conditions and used market clearing conditions.

6. Update COMs for the next period using the current equilibrium sales.

7. Repeat Steps 2-6 ten times to stack ten years of equilibria. Then, compute the average price depreciation rate d_j and premium appreciation b_j throughout the ten years. If the average rates differ from the values used in Step 1 (i.e., if consumers were not rational), then update these rates and return to Step 1.

8. Repeat Steps 2-6 until convergence.

9 Simulation

This section summarizes the simulation outcome using a simple dataset, which has one GV and two (cheap and expensive) EV models. For this practice, we assume the new vehicle market is perfectly competitive, and the new vehicle prices are fixed at \$45,000, \$50,000, and \$80,000 for the GV, cheap EV, and expensive EV, respectively. We simulate 10 years of static equilibria for two scenarios: with and without the used EV credit policy.

The equilibrium outcome for each year consists of 1) consumers' expectations regarding the average price depreciation of EV and GV prices; 2) expectations regarding the increased spread of used EV credit premiums for cheap and expensive EVs; 3) the set of COMs, prices, and sales for each product; 4) used EV premiums for EV models; and 5) scrap rates of vehicles. For instance, in the equilibrium under the credit policy, consumers expect GV and EV prices to decrease by 19.06 percent and 19.87 percent, respectively.

9.1 EV Prices and Premiums with Used EV Credit Policy

With the used EV credit policy, in the equilibrium, consumers expect the premium for cheap and expensive EVs to increase by $385 and $484 per year on average, respectively. Table 3 presents equilibrium prices of cheap EVs over the 10 years of simulation periods. The fluctuations of the equilibrium prices in order periods depend on 1) the supply of EVs with and without available credits and 2) the construction of the initial COMs.

Due to the non-stationary feature of the used EV credit policy, the supply of EVs with credits decreases over periods after the policy's introduction, while that of EVs without credits increases over periods as more EVs consume the credits through transactions. In the initial period of policy introduction, there are no EVs without available credits since all the EVs have not used the credits yet.

The initial COMs, which summarize the ownership structures in the simulation starting period (i.e., end of the data sample period), play an important role in determining the used EV supplies (and equilibrium prices) for the next 20 years. Therefore, having realistic initial COMs is crucial to have realistic equilibrium patterns. For this practice, we only constructed 1 period of data points, and thus, the construction of the initial COMs largely depends on ad-hoc assumptions. However, if we have longer years of data, we have more information to build the initial COMs that summarize the ownership structures at the end of the data sample period.

One noteworthy observation from Table 3 is the presence of used EVs priced exactly at $25,000, which is the maximum price eligible for the used EV credits. Buyers of used EVs prefer to receive these credits at the time of transaction rather than holding the credit option until they resell the vehicle with a future premium because of the time discount on the future utilities. Therefore, the equilibrium prices would be exactly $25,000 for some used EVs.

Table 3: **Equilibrium Prices of Cheap EVs**

Age	1st year	2nd year	3rd year	4th year	5th year	6th year	7th year	8th year	9th year	10th year
New	50000	50000	50000	50000	50000	50000	50000	50000	50000	50000
1	50502	41250	42547	43113	43860	44645	45278	45828	46331	46703
2	54268	51792	43389	44428	44922	45603	46243	46761	47171	47519
3	46005	38927	37150	31532	31951	32125	32430	32727	32991	33217
4	42449	35144	30118	28510	25000	25000	25000	25000	25000	25020
5	39495	35783	30052	25429	25000	23816	24004	24051	24221	24392
6	36037	33692	31084	25775	25000	24257	17673	18033	18335	19015
7	33138	30645	29345	26825	25000	18578	17761	14611	14843	15006
8	31251	28634	27203	25842	25000	19128	15882	15068	12867	13149
9	29443	26669	25109	25000	25000	24852	16310	13675	12942	9533
10	26930	25000	25000	25000	24132	18140	17025	13316	9609	9265
11	25076	25000	25000	23670	16979	16143	15170	14274	9657	7931
12	25000	24955	17256	16157	15082	13772	13270	10528	9853	7564
13	25000	23201	15699	11980	10980	10117	9101	8670	8026	7538
14	24129	16037	14286	10663	9139	8438	7874	6939	6640	6117
15	22591	14961	10787	9272	7880	6633	6168	5674	5024	4858
16	21036	13878	9626	7845	6713	5591	4707	4316	3997	3574
17	19566	12918	8511	6705	5342	4592	3836	3199	2973	2795
18	18136	11758	7317	5498	4352	3534	3092	2609	2246	2131
19	9764	4869	4585	4055	3425	2956	2598	2373	2146	1973

Tables 4 and 5 display the equilibrium premiums for both cheap and expensive EVs, respectively. The premium must be non-negative, as EVs with credits cannot be priced lower than those without credits for the same model and age. Additionally, the credit premium cannot exceed the actual value of the credit, which is \$4k.

Several characteristics indicate the non-stationarity of this policy. Firstly, in the initial year of policy implementation, there exists no used EV credit premium since there are no EVs without credits. The premium reflects the price disparity between EVs with and without remaining used EV credits. Because there are only EVs with credits, the premium cannot exist in the first year. For a similar reason, there are no premiums for young EVs whose price exceeds \$25,000. These EVs cannot utilize the credits through transactions; therefore, they always retain the credits.

Secondly, premiums tend to increase over time as the supply of EVs with remaining credits diminishes while that of EVs without credits increases. During the early periods, consumers can easily find used EVs with remaining credits, thereby making the premium low. However, as the availability of EVs with remaining credits decreases over time, the value of used EVs with credits, compared to those without credits, increases, resulting in a wider price gap (i.e., premium).

Lastly, the used EV credit premiums are higher for cheap EVs than for expensive EVs if their ages are the same, for two reasons. First, it takes a longer time for expensive EVs' prices to reach \$25,000. Therefore, the proportion of expensive EVs with remaining credits compared to those without credits in the market is higher than the proportion of cheap EVs with remaining credits. Therefore, the price gap (i.e., premium) between EVs with and without available credits is higher for expensive models. Second, cheap EVs are purchased by more low-income ($<$ \$75,000) consumers who are eligible for the used EV credits than cheap EVs. Therefore, the value of holding the credit option in the used car market is higher for cheap models than for expensive models.

Table 4: **Equilibrium Premiums of Cheap EVs**

Age	1st year	2nd year	3rd year	4th year	5th year	6th year	7th year	8th year	9th year	10th year
New	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
5	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	2241	2132	2029	1667
7	0	0	0	0	0	2372	2362	2690	2705	2713
8	0	0	0	0	0	2501	2764	2846	2815	2820
9	0	0	0	0	0	0	2836	2866	3018	4000
10	0	0	0	0	0	2617	2603	3002	4000	4000
11	0	0	0	0	2697	2722	2828	2814	4000	4000
12	0	0	2805	2737	2679	2815	2801	4000	4000	4000
13	0	0	2771	4000	4000	4000	4000	4000	4000	4000
14	0	2828	2756	4000	4000	4000	4000	4000	4000	4000
...	...	...	...	...	...	...	...	...	...	...
19	0	4000	4000	4000	4000	4000	4000	4000	4000	4000

Table 5: **Equilibrium Premiums of Expensive EVs**

Age	1st year	2nd year	3rd year	4th year	5th year	6th year	7th year	8th year	9th year	10th year
New	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
9	0	0	0	0	0	0	0	0	0	1946
10	0	0	0	0	0	0	0	0	1925	1923
11	0	0	0	0	0	0	0	0	1931	2296
12	0	0	0	0	0	0	0	1909	1896	2326
13	0	0	0	0	1918	1883	1856	1832	2306	2289
14	0	0	0	1922	1857	2530	2537	2523	2513	4000
15	0	0	2021	1883	2610	3776	4000	4000	4000	4000
16	0	0	2012	3313	4000	4000	4000	4000	4000	4000
17	0	2029	1911	3690	4000	4000	4000	4000	4000	4000
18	0	2516	4000	4000	4000	4000	4000	4000	4000	4000
19	0	2872	4000	4000	4000	4000	4000	4000	4000	4000

10 Counterfactual Policy Evaluation

10.1 Impact on Prices, Sales, and Scrap Rates

Tables 6, 7, and 8 illustrate the percentage changes in equilibrium prices, sales, and scrap rates, respectively, under the used EV credit policy compared to those without the policy. The used EV credits redirect consumer demand from used GVs to used EVs. Consequently, the equilibrium price and sales of GVs decline after the introduction of the credit policy. In contrast, the seller price of used EVs (price plus premium) increases by around 9 percent in the early three periods and by over 14 percent in later periods.

The middle two rows of Table 6 categorize used EVs into cheap and expensive models. The selling price of used EVs increases more for cheap EVs because they are more easily able to utilize the used EV credits, rendering their credits more valuable than those of expensive EVs. Consequently, the price increase resulting from the used EV credit policy is more pronounced for the cheap EV model than for the expensive one. The bottom two rows of Table 6 depict the price impact of the credit policy separately for young used EVs that are not eligible for the used EV credits and for EVs with eligible ages. The selling price of young EVs does not increase substantially due to the used EV credit policy. Conversely, older EVs eligible for the used EV credits experience a 10-20 percent price increase.

Table 7 indicates that EV sales increase by approximately 5-7 percent due to the used EV credit policy. This surge in sales primarily stems from increased purchases by consumers with incomes below \$75,000 who are eligible for the used EV credits. The bottom two rows of Table 7 show the extent to which the EV sales increase is attributable to new EV sales versus used EV sales. Remarkably, new EV sales experience an immediate uptick following the policy introduction, despite the policy tragets on EVs older than 2 years. Used EV credits enhance the resale value of new EVs, rendering them more appealing to car buyers. The policy's impact on used EV sales gradually escalates, up to a 7.5 percent increase in the last year of the simulation period. The supply of used EVs mainly hinges on new EV sales in previous years. Thus, the positive demand shock due to the policy cannot increase the equilibrium quantities of used EVs. Instead, it results in an increase in used EV prices, as observed in Table 6, rather than affecting sales in the early years. However, as more new EVs enter the used car market, used EV sales also increase gradually. Moreover, the higher EV prices reduce the equilibrium scrap rates of used EVs, accelerating the rise in used EV supply in subsequent periods.

Table 8 shows the changes in equilibrium scrap rates for vehicles older than 10 years resulting from the used EV credit policy. The scrap rates of old GVs increase due to the decrease in their prices, albeit with a small percentage increase. On the other hand, the equilibrium scrap rates change in opposite directions for the two groups of EVs: EVs with and without remaining credits. The scrap rates of EVs without credits increase because the equilibrium prices (net of premium) are lower under the credit policy than before, due to the subsidy incidence. It is worth noting that in the first year of policy introduction, there are no EVs without credits, hence the first column of the second row is missing. In contrast, the scrap rates of EVs with available credits experience lower scrap rates due to the used EV credit premium. These rates decline by over 11 percent in the later years of the simulation.

Table 6: **Percent Change in GV and EV Price with Used EV Credit**

	1st year	2nd year	3rd year	...	8th year	9th year	10th year
Used GV price	-0.2%	-0.2%	-0.2%	...	-0.1%	-0.1%	-0.1%
Used EV price + premium	8.9%	9.5%	9.9%	...	14.5%	14.5%	14.3%
Cheap used EV price + premium	13.3%	12.8%	13.9%	...	20.7%	20.8%	20.9%
Expensive used EV price + premium	5.9%	7.3%	7.3%	...	10.9%	10.9%	10.6%
1-2 year old EV price + premium	2.0%	1.6%	1.0%	...	0.9%	0.9%	0.9%
$>$ 2 year old EV price + premium	10.8%	11.8%	12.7%	...	21.0%	21.3%	21.3%

Table 7: **Percent Change in GV and EV Sales with Used EV Credit**

	1st year	2nd year	3rd year	...	8th year	9th year	10th year
GV sales	-0.4%	-0.3%	-0.3%	...	-0.4%	-0.5%	-0.5%
EV sales	5.3%	4.8%	5.3%	...	5.8%	6.9%	7.3%
by cnsmrs with inc $<$ \$75k	11.5%	10.1%	11.8%	...	12.9%	15.0%	15.0%
by cnsmrs with inc $>$ \$75k	3.4%	3.1%	2.9%	...	1.5%	1.7%	2.2%
New EV sales	7.7%	7.5%	7.4%	...	7.1%	7.1%	7.1%
Used EV sales	-0.4%	0.2%	2.3%	...	4.7%	6.8%	7.5%

Table 8: **Percent Change in Old Vehicle Scrap Rates with Used EV Credit**

	1st year	2nd year	3rd year	...	8th year	9th year	10th year
$>$ 10 yr old GV scrap rate	0.0%	0.0%	0.1%	...	0.1%	0.1%	0.1%
$>$ 10 yr old EV scrap rate w/o credits	-	6.0%	8.8%	...	7.9%	5.9%	5.4%
$>$ 10 yr old EV scrap rate with credits	-3.1%	-4.4%	-5.6%	...	-11.8%	-11.7%	-11.6%

Table 9: **Welfare Change with Used EV Credit**

Unit: million $	1st year	2nd year	3rd year	...	8th year	9th year	10th year
Market size	1919	2145	2283	...	3761.9	3611.9	3081.5
Gov't expenditure	114.2	238.3	416.7	...	2152.1	2586.8	2665.7
(Number of issued credits)	(28,544)	(59,574)	(104,184)	...	(538,017)	(646,690)	(666,424)
Consumer surplus	202.9	191.9	233.1	...	179.4	240.4	284.5
CS for those with inc $<$ \$75k	54.0	54.8	87.0	...	136.8	177.9	189.6
CS for cnsmrs with inc $>$ \$75k	148.9	137.1	146.1	...	42.7	62.7	94.9

10.2 Impact on Welfare

In this subsection, we discuss the changes in welfare: consumer surplus and government expenditures on used EV credits. Table 9 presents the changes in welfare in million dollars before and after the used EV credit policy. The actual size of these values is less important since these numbers are from simulation data rather than an actual dataset. However, the patterns of changes provide us with valuable insights into the impact of the used EV credits.

The first row shows the changes in equilibrium market size, which is the sum of price times quantities for all new and used vehicles. Interestingly, the market size increased significantly compared to the government expenditure increase, even in the first year of policy introduction. The increase in market size in the initial period is more than 16 times greater than actual government expenditures for the used EV credits. This is because consumers raise EV prices by taking into account the future value of the credits. In addition, the increase in market size becomes greater in the later years as the rise in new EV sales in the earlier years expands the used vehicle market gradually. Lastly, government expenditure also increases over time as the number of issued credits increases.

The bottom three rows of Table 9 illustrate the increase in consumer surplus resulting from the used EV credit policy. It's worth noting that consumers with incomes higher than \$75,000 also benefit from the credit policy, despite not being eligible for the used EV credit. While they may not directly receive used EV credits, they can still sell their cars at a higher value due to the credit premiums, thereby reducing the efficient per-period rent of cars. However, as time passes, low-income consumers benefit more than high-income consumers as the government allocates more expenditures for the used EV credits, which are exclusively distributed to low-income consumers.

11 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

A.2 Proof of Proposition 1

A.2.1 Incidence of New Vehicle Subsidy

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

$$(1+\theta)\frac{dp_n}{d\tau_n} = \theta\mu + \theta\delta\frac{dp_u}{d\tau_n}. \tag{31}$$

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

$$\frac{dp_u}{d\tau_n} = \frac{D'_n \frac{dp_n}{d\tau_n} - \mu D'_n}{D'_u + R' + \delta D'_n}. \tag{32}$$

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

$$(1+\theta)\frac{dp_n}{d\tau_u} = \theta\delta\frac{dp_u}{d\tau_u}. \tag{33}$$

Totally differentiating the equilibrium condition with respect to τ_u gives

$$\frac{dp_u}{d\tau_u} = \frac{D'_n \frac{dp_n}{d\tau_u} - \mu D'_n}{D'_u + R' + \delta D'_n}. \tag{34}$$

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

A.3 Proof of Corollary 1

The equations in Corollary 1 simplify to

$$\begin{aligned} \frac{dp_n}{d\tau_n} &= \frac{dp_n}{d\tau_u} \\ \frac{dp_u}{d\tau_n} &= \frac{dp_u}{d\tau_u} - 1. \end{aligned} \tag{35}$$

The top line follows from the top line of Proposition 1. The bottom line follows from rearranging the bottom line of Proposition 1.

B Reduced-Form Evidence Appendix

B.1 Tests of Anticipation Effects Before January 2023 Implementation

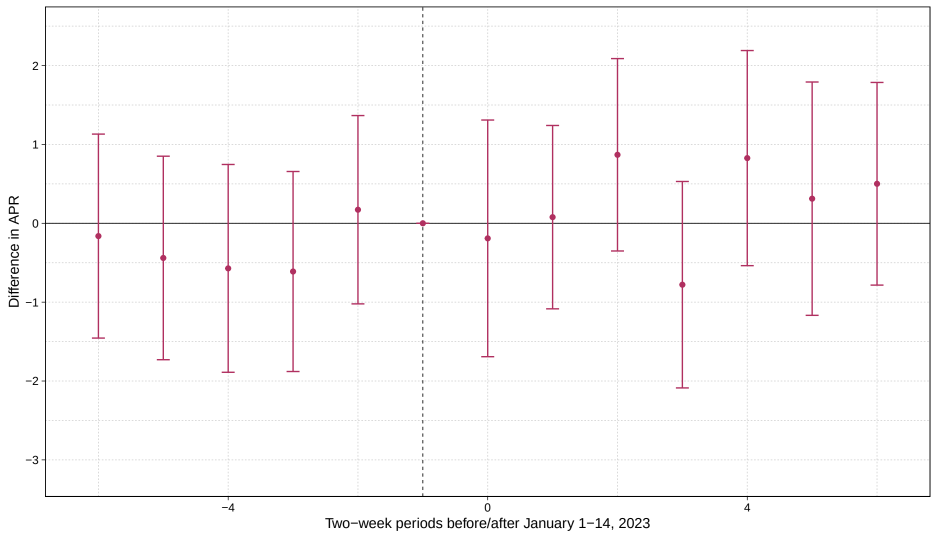
The goal of this section is to assess potential effects of the tax credit on the used vehicle market through channels other than transaction prices. For example, it could be that dealerships change financing terms rather than the upfront price of a vehicle in response to the policy. Because the tax credit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

B.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 5.2 with APR as the outcome variable and standard errors clustered at the model by model year level. We do not see evidence of a change in the financing terms, showing that the price event studies are indicative of the true cost of the transaction to consumers.

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

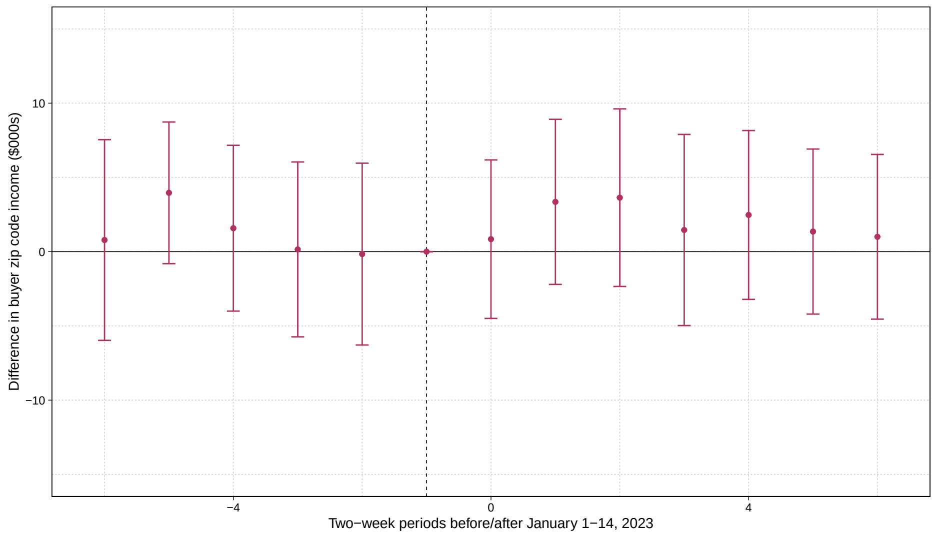


B.1.2 Buyer Income

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 5.2 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. This lends further evidence that the pre and post-periods consist of comparable transactions.

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



B.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:

$$q_{kyt} = EV_k + G_{ky} + (EV_k \times G_{ky}) + \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^1 G_{ky} \mathbb{1}\{s + t = \tilde{T}\} + \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^2 EV_k \mathbb{1}\{s + t = \tilde{T}\}$$
$$+ \sum_{s=T_{\text{pre}}}^{T_{\text{post}}} \gamma_s^3 G_{ky} EV_k \mathbb{1}\{s + t = \tilde{T}\} + (\lambda^{make_k} \times \lambda^t) + \lambda^k + \lambda^y + \epsilon_{kyt} \tag{36}$$

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**

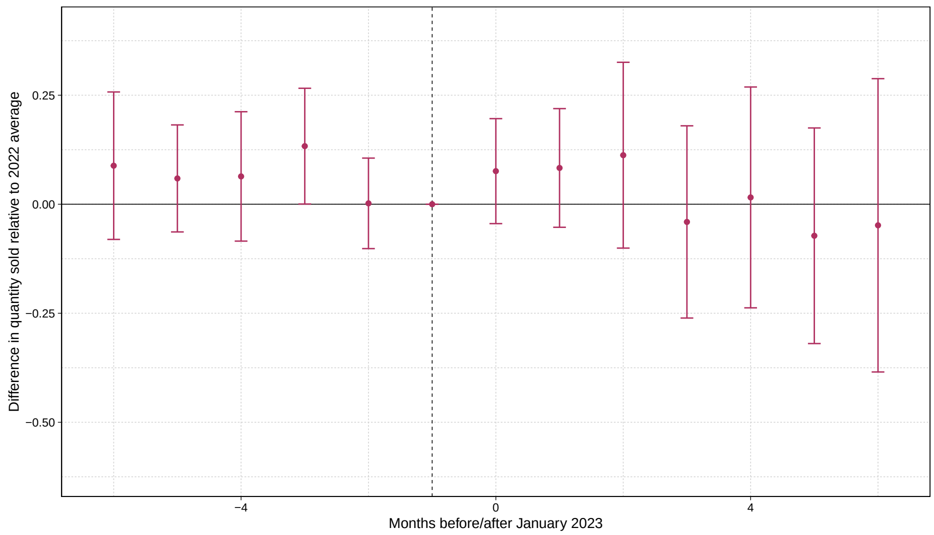


Figure A4 shows the raw total transactions for each treatment group. The y-axis on the left shows the quantity for EVs, and the y-axis on the right is shifted down to show the quantity for GV. As discussed above, we can see that the quantity for expensive EVs is increasing over time, with a jump at the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

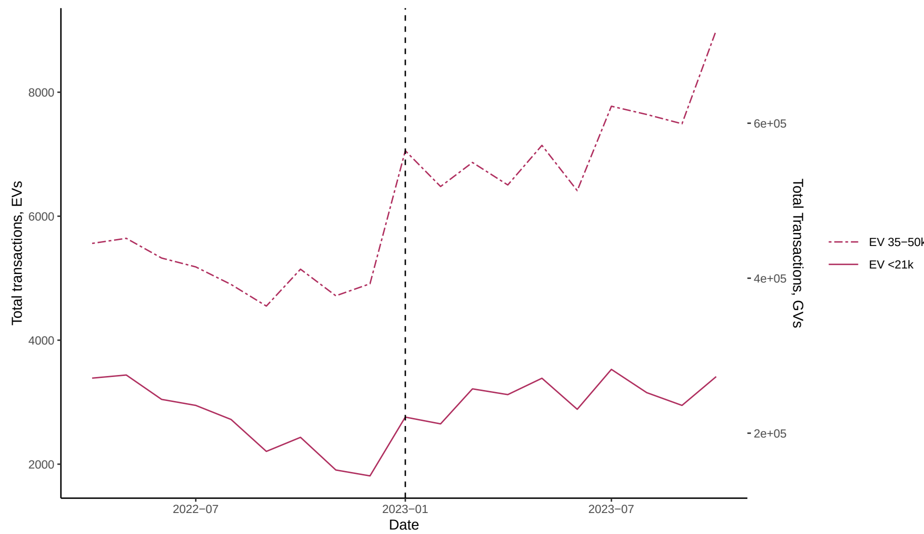
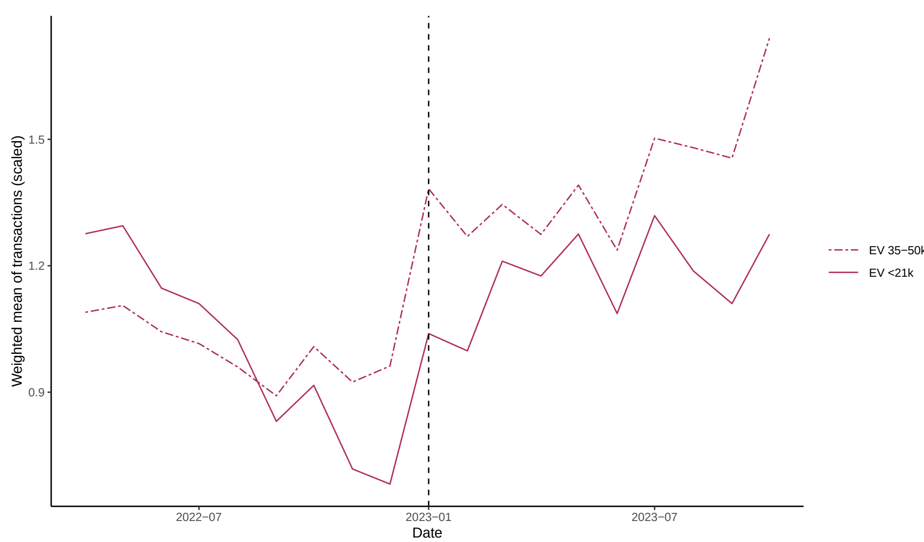


Figure A5 shows the average scaled transaction quantity for each group. While the average scaled transaction quantity for cheap EVs is lower in December 2022 than in January 2023, it is following a pre-existing trend for this group. As we see in the raw totals above, this decrease is occurring for cheap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

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

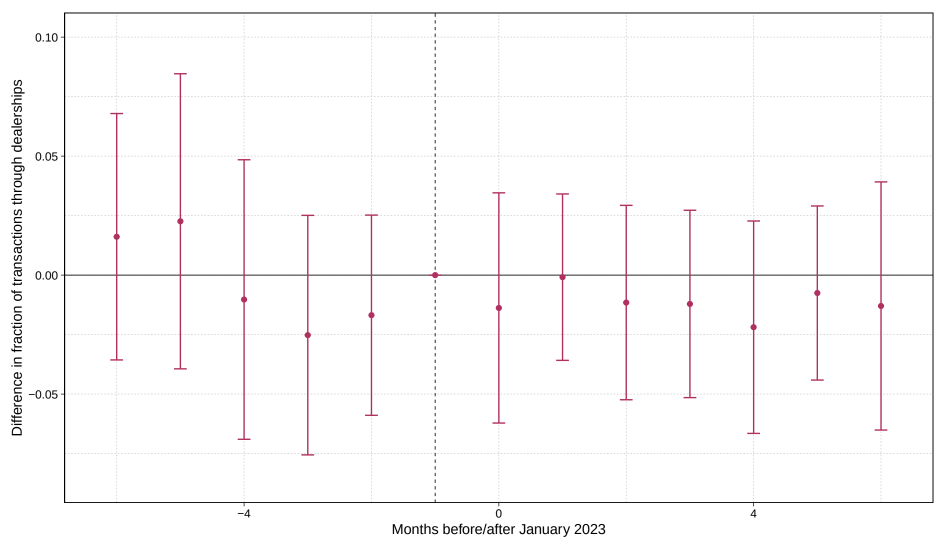


B.1.4 Changes in Dealership Transaction Shares

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 B.1.3, we focus on this second explanation.

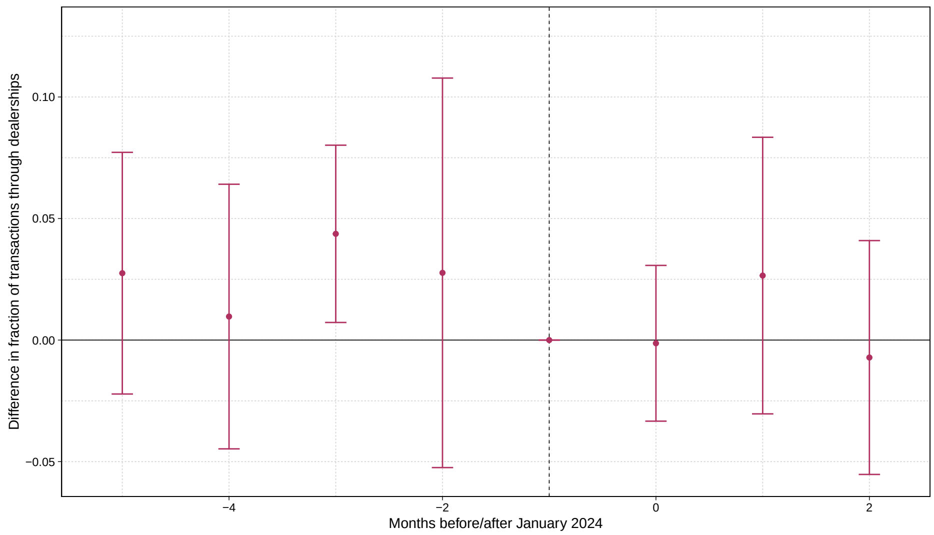
We apply the empirical strategy from Section B.1.3 with dealership share of transactions as the outcome variable. Figure A6 shows the results of this triple-difference event study specification around the 2023 policy event. We do not see evidence that the dealership share of transactions responded to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



B.2 Measuring Excess Bunching

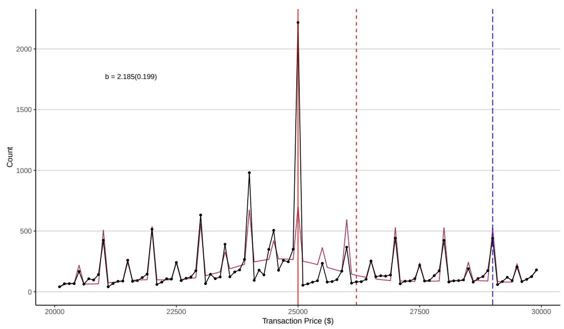
The goal of this section is to quantify the excess mass in the transaction price distribution under \$25,000 shown in the descriptive analysis in Section 5.3. Comparing excess mass across 2023 and 2024 can help us identify the extent to which the dealership credit transfer increased the value of credits 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.

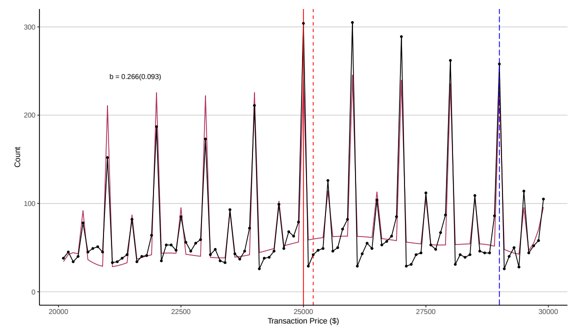
Figure A8 shows an example of this analysis for the transaction price distribution of EVs in 2022 and 2024. The black line shows the values from the data and the solid red line shows the counterfactual distribution constructed as described above. The red dotted lines show the upper bound of the missing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