IRA Tax Credit for Used Electric Vehicles

Hunt Allcott Hyuk-soo Kwon Tess Snyder

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Abstract

The Inflation Reduction Act (IRA) provides tax credits for purchasing used electric vehicles (EVs), aiming to address concerns that new EV tax credits predominantly benefit wealthier buyers. Our analysis begins with an estimation of the pass-through of these used EV tax credits, employing quasi-experimental methods on confidential microdata of transaction prices from auto dealerships. Event study estimates reveal little evidence of changes in used EV prices after the IRA was enacted and the tax credits became available, suggesting that the economic incidence falls primarily on EV buyers. However, we find evidence of bunching in transaction prices below the $25,000 price threshold, implying some incidence on sellers. Furthermore, we assess the efficiency and distributional impacts of the tax credits using a structural model for both new and used vehicle markets. This dynamic model tracks the proportion of vehicles that have not yet claimed the one-time transaction credit, which diverges from standard dynamic models that depend on stationarity assumptions. Our model integrates automakers' pricing strategies, consumers' vehicle choices, car owners' scrappage decisions, and the price premium for individual vehicles that have not yet claimed the credit. Using this model, we simulate the outcomes of the used EV tax credits and compare these with other policy interventions, such as means-tested new EV subsidies that are also designed to equitably increase electric vehicle sales.

Keywords: Electric Vehicle, Used EV Subsidy, Durable Goods

1 Introduction

The Inflation Reduction Act (IRA) marks a significant change in U.S. energy policy by offering tax incentives for used electric vehicles (EVs). This policy aims to broaden access to green technologies, whereas subsidies for new EVs tend to primarily benefit wealthier consumers. Our study explores how these used EV tax credits affect consumer costs and the dynamics of the used vehicle market. Our analysis employs quasi-experimental approaches to examine transaction price data from auto dealerships, assessing the pass-through of the IRA's used EV tax credits. The results show small immediate impact on used EV prices after the IRA is implemented, suggesting that EV buyers mainly reap the economic benefits. Additionally, we observe price clustering below the $25,000 threshold, likely because sellers were adjusting prices to ensure vehicles qualify for the tax credits.

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 internal combustion engine vehicles (ICEs) to used EVs, leading to a decrease in both the equilibrium price and sales of ICEs. 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 ICEs 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.

2 Literature Review

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.

3 Data and Policy Background

3.1 Data

We have micro-data on vehicle sales and transactions for California statewide and the U.S. nationwide.

Our California data is based on the statewide vehicle registration system snapshots provided by the California Department of Motor Vehicles (DMV). A snapshot records all the vehicles registered at the California DMV system at a given time, and we rely primarily on 3 snapshots taken in October 2022, October 2023, and January 2024. All the snapshots are at the vehicle level, and for each vehicle, we observe the vehicle identification number (VIN) prefix, make, model, trim, model year, dates (accurate to year month) of all transactions, and odometer reading and self-reported price from the most recent transaction. With the NHTSA (2023) VIN decoder, we additionally have the body class, vehicle weight, and powertrain type for each vehicle.

Table 1: California DMV snapshots combined: Oct 2022 and Oct 2023

	Mean	Std. dev.	Min.	Max.	Obs.
Price ($000s)	22.2	18.4	0.0	96.7	76,739,599
EV	0.04	0.19	0	1	76,742,404
Mileage (000 miles)	43	53	0	500	74,515,511

Cox Automotive provides vehicle retail transaction data, collected from all partnered dealerships across the states from July 2021 to November 2023. The Cox data is at the transaction level, and for each transaction, we observe the VIN, dealer-reported total transaction price, applicable rebates, date, days on lot before transaction, odometer reading, dealership identifier, and the buyer's ZIP code. We also apply the NHTSA VIN decoder to obtain additional vehicle characteristics. We use a balanced panel of dealerships in our descriptive evidence.

Table 2: Cox transaction-level used vehicle retail data

	Mean	Std. dev.	Min.	Max.	Obs.
Price ($000s)	29.9	18.6	0.0	960.0	15,046,119
EV	0.01	0.12	0	1	15,658,413
Mileage (000 miles)	53	39	0	500	14,779,164

For the demand estimation, we use data from the California DMV from 2022 and 2023. An observation consists of the transaction history of a vehicle. We aggregate the vehicle stock volume to the make-body type-fuel type-model year level for 2022 and 2023 separately, and we aggregate the transfer volume to this observation level for the whole time period. We take the median price within this category as the sale price. We drop transactions for vehicles older than 20 years and make-body type-fuel type combinations with non-consecutive model years.

3.2 Policy Background

The Used Clean Vehicle Credit from the Inflation Reduction Act (IRA) was announced on August 16, 2022 and went into effect on January 1, 2023. It is a tax credit for the purchase of a pre-owned electric or plug-in hybrid vehicle equaling 30% of the sale price up to a maximum level of $4,000. To claim this tax credit, the buyer's income must be below a threshold amount. The income threshold is $150,000 for married couples filing jointly, $112,500 for heads of households, and $75,000 for all others. There are also restrictions on the vehicle and sale in order to claim the tax credit. The sale price of the vehicle must be $25,000 or less, and the purchase must be made from a licensed dealer. The battery capacity of the vehicle must be at least 7 kilowatt hours. 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 model year must precede the year of purchase by at least 2 years, and the vehicle cannot have already been transferred after August 16, 2022 to a qualified buyer.

Prior to 2024, this tax credit must be claimed while filing taxes. Starting on January 1, 2024, this

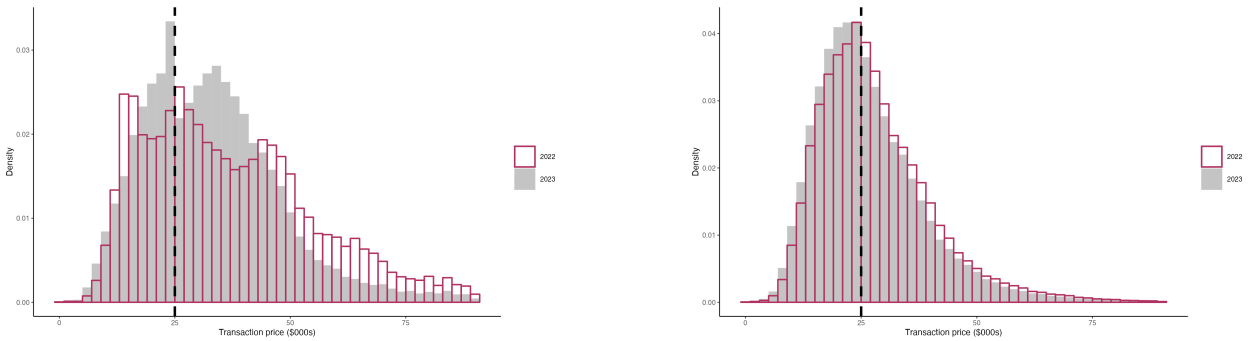
credit may be applied at the point of sale. This means that a buyer can transfer the credit to the dealer and either pay a lower price or receive cash equivalent. The dealer must register with the IRS to receive an advance payment of the value of the credit.

3.3 Descriptive Evidence

Given the sale price cutoff for the tax credit, we use evidence from the distribution around $25,000 to understand whether and to what extent the tax credit impacted sale prices in the used vehicle market. This is an important step towards measuring the tax incidence of this policy. If the tax credit did not impact prices, we would not expect to see any excess bunching around $25,000 for electric vehicles in 2023 once the credit is in place. Any excess bunching indicates a shift in prices.

We expect prices of qualifying vehicles that counterfactually would have been sold for less than $25,000 to weakly increase due to the Used Clean Vehicle Credit. The increased prices would likely not exceed $25,000 because then the vehicle would lose the benefit of the tax credit. The extent of the pass-through of this tax credit will depend on the share of buyers that are eligible, vehicle substitution patterns, and bargaining between the dealer and buyer. This tax credit may also impact the prices of vehicles that counterfactually would have been sold at prices higher than $25,000 due to competition within the used vehicle market and other incentives of car dealers. A seller may prefer to sell sooner due to uncertainty or other hassle costs associated with holding a vehicle for a longer period of time. Price bunching at $25,000 indicates that either or both of these forces are present due to the tax credit.

If we could compare the price distribution under the tax credit to the counterfactual price distribution, the bunching at $25,000 that comes from the counterfactual distribution below $25,000 would provide information about the pass-through. As an initial step, we compare the price distributions before and after the implementation of the policy at the start of 2023 across used electric and gas vehicles.



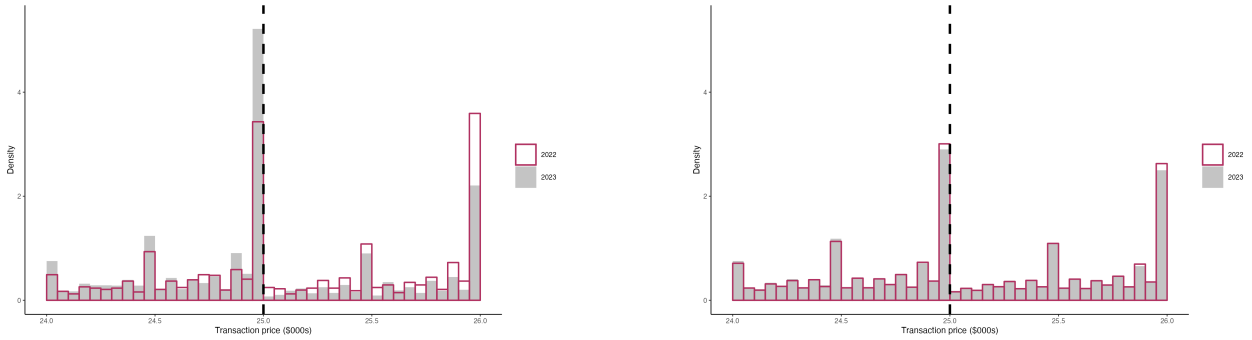
(a) Electric vehicles

(b) Gas vehicles

Figure 1: Sale price distribution for used vehicles

Figure 1 shows the sale price distribution for vehicle transactions in the Cox Automotive data separated by fuel type and year. As expected, we do not see any significant changes between 2022 and 2023 around the $25,000 threshold for gas vehicles. The price distributions in 2022 and 2023 for electric vehicles show more significant changes. We see shifts in the distribution both above and below the $25,000 threshold with noticeable bunching just below. Figure 2 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 2023 exceeds the 2022 value for electric vehicles. To a smaller extent, there is also greater mass at $24,000 and $24,500 in 2023 for electric vehicles.



(a) Electric vehicles

(b) Gas vehicles

Figure 2: Sale price distribution around the $25k cutoff

Appendix A uses an event study analysis around both the policy announcement in August of 2022 and the policy implementation in January of 2023 to show that used electric vehicle have a limited price response in the short-run. This indicates that the price response suggested by bunching under $25,000 may occur over the long run.

4 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, style, 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 the number of consumers holding each vehicle type that reach the end of their holding time in period t net of the scrapped vehicles. Prices are set to clear the market.

4.1 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, suppressing the notation t for simplicity.

Because consumer i expects to resell or scrap the vehicle at the end of the holding time, the utility of purchasing vehicle j of age a is given by

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

where ρ is the time discount factor, P_{ija} represents the price disutility for consumer i from purchasing vehicle j of age a and $-\rho^{h_i} P_{ija+h_i}$ is the benefit of reselling or scrapping the vehicle at the end of

the holding period. We parameterize the one-period utility as $\widetilde{u}_{ija} = X_j\beta_i + \beta_i^a a + \varepsilon_{ija}$, where X_j is a vector of characteristics, β_i^a is an age disutility parameter, and ε_{ija} is a Type I Extreme Value shock.

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 assume consumer i makes the scrap decision at the end of $t + h_i - 1$ and sells the car at $t + h_i$ if not scrapped. We can then rewrite the present value of purchasing vehicle j as

$$\begin{aligned} U_{ija|h_i} &= \sum_{k=0}^{h_i-1} \rho^k \widetilde{u}_{ija} + \sum_{k=1}^{h_i-1} \rho^k \beta_i^a + \alpha_i p_{ja} - \alpha_i \rho^{h_i}[(1 - g_{ja+h_i-1})d_j^{h_i} p_{ja} + g_{ja+h_i-1}\underline{p}_j] \qquad (2) \\ &= \sum_{k=0}^{h_i-1} \rho^k \widetilde{u}_{ija} + \sum_{k=1}^{h_i-1} \rho^k \beta_i^a + \alpha_i[(1 - \rho^{h_i}(1 - g_{ja+h_i-1})d_j^{h_i})p_{ja} - \rho^{h_i} g_{ja+h_1-1}\underline{p}_j] \end{aligned}$$

where α_i is the price coefficient for consumer i, g_{ja} is the scrap probability, $\underline{p}_j$ is the scrap value, and d_j is the expected depreciation rate for the price of vehicle type j. Consumers' anticipation of future prices is incomplete in that $p_{ja+h_i} = d_j^{h_i} p_{ja}$ and $g_{ja+h_i-1} = g_{ja+h_i-1}(d_j^{h_i-1} p_{ja}) = \zeta_{ja+h_i-1} \cdot [d_j^{h_i-1} p_{ja}]^\eta$.

We can now rescale the equations above to define individual utility as

$$\begin{aligned} u_{ija|h_i} &= \widetilde{u}_{ija} + \beta_i^a \frac{\sum_{k=1}^{h_i-1} \rho^k}{1+\sum_{k=1}^{h_i-1} \rho^k} + \alpha_i \frac{[1-\rho^{h_i}(1-g_{ja+h_i-1})d_j^{h_i}]p_{ja} - \rho^{h_i} g_{ja+h_i-1}\underline{p}_j}{\sum_{k=1}^{h_i-1} \rho^k} \qquad (3) \\ &= \widetilde{u}_{ija} + \beta_i^a A_{ija} + \alpha_i B_{ija} \qquad (4) \end{aligned}$$

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

$$u_{ija} = X_j\beta_i + \xi_j + \beta_i^a(a_j + A_{ija}) + \alpha_i B_{ija} + \varepsilon_{ija} \qquad (5)$$

where $\beta_i^a = \beta_1^a + \beta_2^a h_i$, $\alpha_i = \frac{\alpha}{inc_i}$, and

$$\begin{aligned} A_{ija} &= 1 - \frac{1}{\sum_{k=1}^{h_i} \rho^{k-1}} \\ B_{ija} &= \frac{[1 - \rho^{h_i}(1 - g_{ja+h_i-1})d_j^{h_i}]p_{ja} - \rho^{h_i} g_{ja+h_i-1}\underline{p}_j}{\sum_{k=1}^{h_i} \rho^{k-1}} \end{aligned}$$

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

$$u_{i0} = 0. \qquad (6)$$

Since we draw a single logit error 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.

4.2 Scrappage Decision

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

$$y_{jat} = \frac{N_{jat} - N_{ja+1,t+1}}{N_{jat}} \tag{7}$$

where N_{jat} is the total stock of model j aged a in period t.

For consumer choices, the relevant scrappage probability 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,

$$(1 - g_{jat})n_{jat} = n^o_{ja+1,t+1} \ , \ g_{jat}n_{jat} = N_{jat} - N_{ja+1,t+1} \tag{8}$$

where $n^o_{ja+1,t+1}$ is the number of vehicles of vehicle j with age a that we observe being traded in period t and $N_{jat} - N_{ja+1,t+1}$ is the number of scrapped vehicles.

We assume that the consumer scrap decision depends on the resale price. 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 this relationship as

$$\zeta_{jat} p^{\eta}_{jat} = g_{jat} \tag{9}$$

where η represents the price elasticity of the scrap decision and ζ_{jat} scales this relationship.

4.3 Supply of New Vehicles

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

$$\pi_{f,t} = \max_{\{p_{j,a,t} | a=0, \ j \in J_{f,t}\}} \sum_{j \in J_{f,t}} (p_{j,0,t} - mc_{j,t}) \ Q(\boldsymbol{p}_{0,t}, \boldsymbol{p}_{a>0,t}, \boldsymbol{q}_{a>0,t}) \tag{10}$$

where $\boldsymbol{p}_{0,t}$ 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.

4.4 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.

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

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 first column of COM and scrap probabilities dictate the used vehicle supplies for vehicle j in the subsequent period. To be specific, the supply of model j with age $a+1$ in the next period is equal to $\Omega^j_{a1} \times (1 - g_{ja})$.

5 Estimation

5.1 Depreciation Rates

We calculate the expected depreciation rate d_j as the average percent change in price between each model year within a vehicle category.

$$d_j = \frac{\sum_{a=\min a_j+1}^{\max a_j} (p_{j,a-1} - p_{j,a})/p_{j,a-1}}{\max a_j - \min a_j} \tag{11}$$

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 electric vehicles, and one for gas-powered vehicles-that are calculated as follows:

$$d_F = \frac{\sum_{j \in \mathcal{J}_F} \sum_{a=\min a_j+1}^{\max a_j} (p_{j,a-1} - p_{j,a})/p_{j,a-1}}{\sum_{j \in \mathcal{J}_F} 1} \tag{12}$$

where $F \in EV, ICE$ 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.

5.2 Scrap Values and Probabilities

The scrap values and probabilities are necessary to calculate the expected average rental price of vehicle j of age a for consumer of holding type h_i.

From Equation 8, we calculate the scrap probabilities based on the observed stock of vehicle j of age a in 2022, $N_{ja,2022}$, compared with the stock of vehicle j at age $a+1$ in 2023, $N_{ja+1,2023}$. Note

that we do not observe the $n_{ja,2022}$ but rather the observed transfer volume, and so we calculate $g_{ja,2022}$ as

$$g_{ja,2022} = 1 - \frac{n^o_{ja+1,2023}}{N_{ja,2022} - N_{ja+1,2023} + n^o_{ja+1,2023}}. \tag{13}$$

where $n^o_{ja+1,2023}$ is the transfer volume in the 2022 and 2023 snapshot. We set $g_{j\max a_j,2022} = 1$ so that the probability of scrapping the oldest vehicles is 100%. Because this calculation is based on registrations in California, we assume that inflows and outflows from the state balance out at the aggregate level.

To estimate ζ_{jat} and η from Equation 9, we regress $\log(g_{ja,2022})$ on $\log(p_{ja})$:

$$\log(g_{ja}) = c + \eta \log(p_{ja}) + \epsilon_{ja} \tag{14}$$

where we construct ζ_{ja} as $\zeta_{ja} = \exp(c + \epsilon_{ja})$. This relationship allows us to calculate the scrap rates and rents in the counterfactual analysis based on the equilibrium prices.

We set the scrap value $\underline{p}_j$ as half of the expected price at the maximum age for all vehicles $\bar{a}$. We set $\bar{a} = 20$. Since we do not observe all vehicle types at age 20, especially for electric vehicles which have been introduced to the market more recently, we construct $\underline{p}_j = d_j^{20-\min a_j} p_{j\min a_j}$ using the depreciation rate calculated above.

5.3 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:

$$\#\text{ of consumers with holding time of 1 year : 2 years : 3 years : } \ldots \text{ : T years} = c_1 : 2{\cdot}c_2 : 3{\cdot}c_3 : \ldots : T{\cdot}c_T \tag{15}$$

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

5.4 Demand Parameters

From our utility specification in Equation 5, we need to estimate $(\alpha, \beta_0, \beta_1^a, \beta_2^a)$ in the following equation:

$$u_{ija} = \beta_0 + (\beta_1^a + \beta_2^a h_i)(a_j + A_{ija}) + \frac{\alpha}{inc_i} B_{ija} + \varepsilon_{ija} = \delta_j + \beta_2^a h_i (a_j + A_{ija}) + \frac{\alpha}{inc_i} B_{ija} + \varepsilon_{ija} \tag{16}$$

where we set $\rho = 0.97$ to calculate the age adjustment value A_{ija} and use the depreciation rates and scrappage parameters to construct the average rent B_{ija} as follows:

$$A_{ija} = 1 - \frac{1}{\sum_{k=1}^{h_i} \rho^{k-1}}$$
$$B_{ija} = \frac{[1 - \rho^{h_i}(1 - g_{ja+h_i-1})d_{F_j}^{h_i}]p_{ja} - \rho^{h_i} g_{ja+h_i-1}\underline{p}_j}{\sum_{k=1}^{h_i} \rho^{k-1}}.$$

The choice set for each consumer is determined by their holding time h_i and $\max a = 20$. In order to calculate B_{ija} for consumers with various holding times, we need to have g_{ja} for each vehicle at all possible ages. As discussed above, we do not observe each vehicle type at all ages and so cannot directly calculate the scrappage probability across all ages from the data. In order to extrapolate from the observed combinations of j and a to all possible combinations of j and a, we construct g_{ja} based on Equation 8 using the parameters estimated above. We construct a prediction for the out-of-sample ζ_{ja} based on the observed ζ_{ja} as follows:

$$\zeta_{ja} = \sum_j \gamma_j \text{Model Year}_a + FE_j + \epsilon_{ja} \tag{17}$$

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 regress the implied δ on the vector of characteristics $X = (1, a)$ to find (β_0, β_1^a). Finally, we match the model-predicted fraction of new vehicles bought and then re-sold by consumers with holding time of 1 year to the observed fraction to identify β_2^a. We find the observed fraction of new vehicles purchased by consumers with holding time of 1 year by dividing the transfer volume of 1-year-old vehicles over the stock of 1-year-old vehicles. The intuition here is that β_2^a governs the relationship between holding time and age preference. If consumers with shorter holding times have a greater disutility from age, we will observe a higher proportion of consumers with $h_i = 1$ purchasing new vehicles. The utility setup assumes that this preference is monotonic in holding time. We then iterate over these parameters until errors are minimized.

Table 3: Demand calibration inputs

Parameter	Value
ρ	0.97
Avg. price elasticity	-5.06
d_{EV}	0.921
d_{ICE}	0.856
η	-2.16

5.5 Estimation Results

A positive β_2^a implies that consumers with shorter holding times prefer younger vehicles.

Table 4: Scrap probability results

	$\log(g_{ja})$
Intercept	1.54
	(0.24)
$\log(p_{ja})$	-2.16
	(0.08)

Table 5: Demand calibration results

	(1)
α	31.8
β_1^a	-3.24
β_2^a	0.998
β_0	-17.8

6 Equilibrium Analysis

6.1 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 \$100k, 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 \$25k, 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.

6.2 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. 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**

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

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.

6.3 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,[1] 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:

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

$$D_{jat}(p_{jat}, l_{jat}) + \widetilde{D}_{jat}(p_{jat}, l_{jat}) = \Omega_{a1}^{jt} + \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a > 0 \tag{18}$$

   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

$$D_{jat}(p_{jat}, l_{jat}) : \widetilde{D}_{jat}(p_{jat}, l_{jat}) = \Omega_{a1}^{jt} : \widetilde{\Omega}_{a1}^{jt} \text{ for all } j \text{ and } a \tag{19}$$

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

[1] 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.

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.

7 Simulation

This section summarizes the simulation outcome using a simple dataset, which has one ICE 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 \$45k, \$50k, and \$80k for the ICE, 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 ICE 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 ICE and EV prices to decrease by 19.06% and 19.87%, respectively.

7.1 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 6 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 6 is the presence of used EVs priced exactly at $25k, 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 $25k for some used EVs.

Table 6: Equilibrium Prices of Cheap EV

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 7 and 8 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 $25k. 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 $25k. Therefore, the proportion of expensive EVs with remaining credits compared to those without credits in the market is higher than the proportion of cheap EVs with remaining credits. Therefore, the price gap (i.e., premium) between EVs with and without available credits is higher for expensive models. Second, cheap EVs are purchased by more low-income ($< \$75$k) 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 7: Equilibrium Premiums of Cheap EV

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 8: Equilibrium Premiums of Expensive EV

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

8 Impact of Used EV Credit Policy

8.1 Impact on Prices, Sales, and Scrap Rates

Tables 9, 10, and 11 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 ICEs to used EVs. Consequently, the equilibrium price and sales of ICEs decline after the introduction of the credit policy. In contrast, the seller price of used EVs (price plus premium) increases by around 9% in the early three periods and by over 14% in later periods.

The middle two rows of Table 9 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 9 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% price increase.

Table 10 indicates that EV sales increase by approximately 5-7% due to the used EV credit policy. This surge in sales primarily stems from increased purchases by consumers with incomes below \$75k who are eligible for the used EV credits. The bottom two rows of Table 10 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% 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 9, 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 11 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 ICEs 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% in the later years of the simulation.

Table 9: % Change in ICE and EV Price with Used EV Credit

	1st year	2nd year	3rd year	...	8th year	9th year	10th year
Used ICE 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 10: % Change in ICE and EV Sales with Used EV Credit

	1st year	2nd year	3rd year	...	8th year	9th year	10th year
ICE 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 11: % 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 ICE 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 12: 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

8.2 Impact on Welfare

In this subsection, we discuss the changes in welfare: consumer surplus and government expenditures on used EV credits. Table 12 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 12 illustrate the increase in consumer surplus resulting from the used EV credit policy. It's worth noting that consumers with incomes higher than $75k 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.

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Online Appendix

A Short-Term Event Studies

In this section, we present preliminary findings based on reduced-form event studies on vehicle price response to credit availability.

With the IRA Used Clean Vehicle Credit announced in August 2022 and coming into effect starting from Jan 2023, it is possible that the vehicle market respond immediately. When the policy was announced, a buyer might exhibit a higher willingness to pay for the same vehicle foreseeing an increase in possible resale value. A similar effect can be expected around the policy passage date as well. We suspect such on-impact responses, if any, can be observed in the vehicle prices within narrow windows around the two event times.

We run the following two-way fixed-effect event study on our transaction-level Cox data:

$$y_{ijt} = \sum_{k=T_{\text{pre}}}^{T_{\text{post}}} \gamma_k D_{ijt} \mathbb{1}\{k + t = \tilde{T}\} + \alpha_i + \delta_t + \varepsilon_{ijt}, \tag{20}$$

where y_{ijt} is the price of transaction j of vehicle model-year i in period t, D_{ijt} is the treatment indicator, $\mathbf{1}\{k + t = \tilde{T}\}$ is the time to treatment indicator, γ_k estimates effect for period k, and α_i and δ_t are option (combination of model, model year, and powertarain) and weekly time fixed-effects.

We acknowledge assigning D based on the actual EV transaction price would be misleading since the price decision is directly related to the policy. We propose to use predicted price to assign D instead, where the predicted price is based on

$$p_{ijt} = odo_{ijt} + (t - t_0) \cdot \sum_n \mathbb{1}\{MY_i = n\} + \alpha_i + \lambda_j + \epsilon_{ijt} \tag{21}$$

where *odo* is the mileage at the time of transaction, $(t - t_0) \cdot \sum_n \mathbb{1}\{MY_i = n\}$ captures the model-year-specific linear trend in price by setting t_0 to be the start time of the data, α_i represents option fixed-effects, and λ_j represents buyer's location fixed-effects.

We classify vehicles into three categories based on their predicted transaction price $\hat{p}$: economic vehicles are those with $\hat{p}$ below \$21,000, entry-level luxury vehicles are those between \$25,000 and \$45,000, and luxury vehicles are those above \$45,000. This allows us to see the change in EV price relative to their comparable ICE vehicle substitutes, which leads to three event study designs. For economic vehicles, we look at the subset of transactions with $\hat{p}$ in the range, assign $D = 1$ for all EV transactions and $D = 0$ for all ICE vehicle transactions, and run the regression above. The event studies for entry-level luxury and luxury vehicles follow the same procedure. For each class of vehicle, we run the regression with five pre-periods and five post-periods, separately around the policy announcement date and implementation date.

Results are presented in Figure 3, 4, and 5. We find the event studies suggest there is a lack of evidence of used EV price increase on-impact either after policy announcement and implementation. Experimenting with more complicated specifications such as controlling vehicle age or setting the outcome to be the natural log of price, we observe similar overall trends.

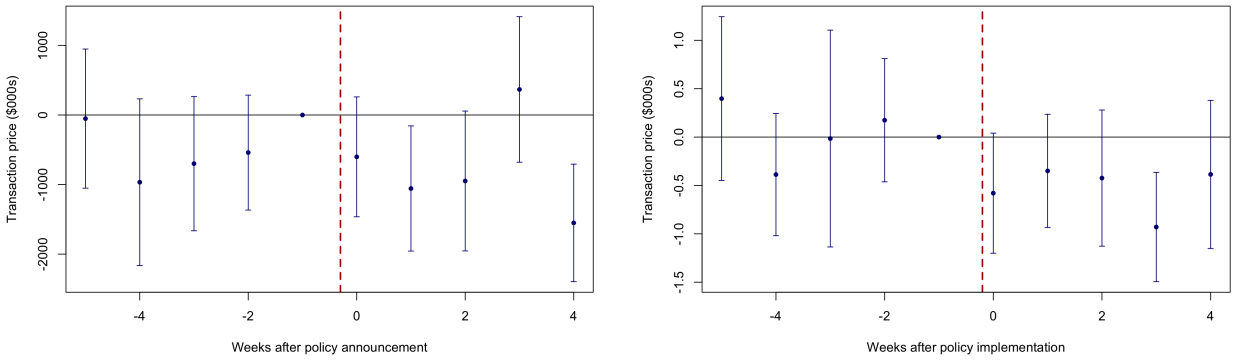


Figure 3: Vehicles with predicted price below $21,000

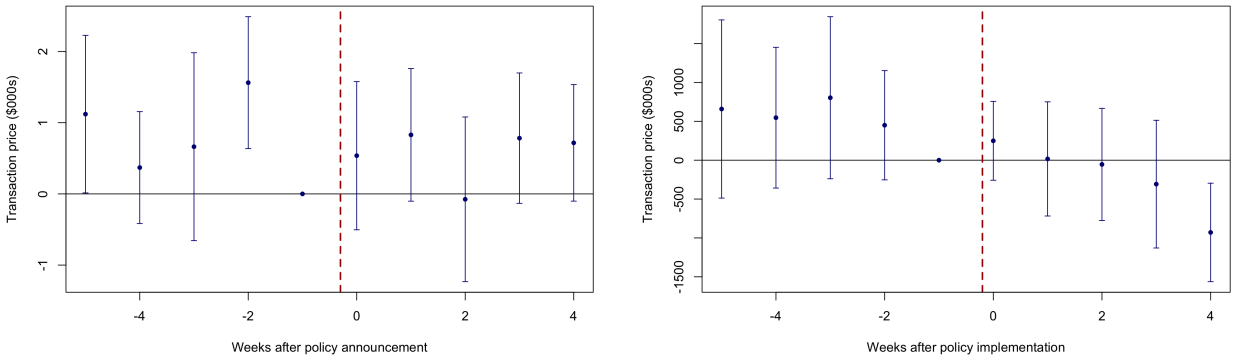


Figure 4: Vehicles with predicted price above $25,000 below $45,000

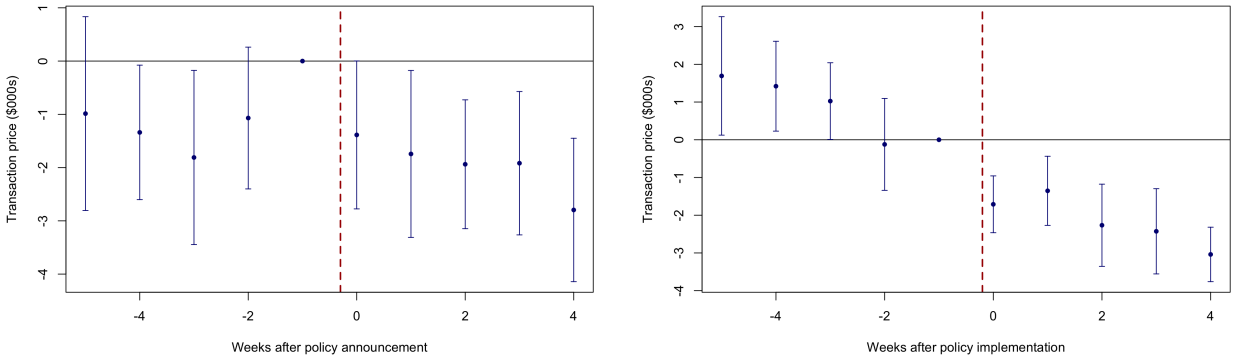


Figure 5: Vehicles with predicted price above $45,000