Vehicle Price Depreciation: An Empirical Study on Used EVs vs ICEVs in the United States

by

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Abstract

The transition to light-duty electric vehicles (EVs), including battery electric vehicles (BEVs), plug-in hybrids (PHEVs), and hybrid electric vehicles (HEVs), is a critical strategy for decarbonizing the transportation sector and reducing greenhouse gas emissions. While new EVs typically have higher upfront costs compared to internal combustion engine vehicles (ICEVs), the growing used EV market offers a potential pathway to broader affordability. This study aims to quantify price depreciation patterns of EVs relative to ICEVs to better understand barriers to secondary market adoption. Using a dataset of approximately 150,000 vehicle listings scraped from Craigslist across 17 major U.S. cities, we developed a log-linear regression model to estimate vehicle retention rates, defined as the ratio of listed price to the manufacturer's suggested retail price (MSRP). Key explanatory variables include vehicle age, mileage, powertrain type, vehicle class, seller type, MSRP, and geographic location. Additional models incorporate interaction terms and brand-specific effects to examine variation in depreciation behavior, with a focused comparison between Tesla and non-Tesla BEVs. Results show that BEVs generally exhibit lower retention rates than ICEVs, especially within the first 10 years. During this period, PHEVs and HEVs also exhibit better retention rates than BEVs. Moreover, Tesla electric vehicles start with higher initial retention but depreciate more quickly than their non-Tesla BEV counterparts. Additionally, regional variation was also observed. These findings suggest that while the used EV market is expanding, depreciation remains a significant economic factor affecting EV adoption. Understanding these trends can inform consumer decision-making, policy design, and manufacturer pricing strategies in support of a sustainable transition to electric mobility.

KEYWORDS

Retention Rate, Used Vehicles, Depreciation, Battery Electric Vehicles, Plug-in Hybrid Electric Vehicles

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List of Acronyms

ICEV	Internal Combustion Engine Vehicle
BEV	Battery Electric Vehicle
EV	Electric Vehicle
HEV	Hybrid Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
LDV	Light Duty Vehicle
MY	Model year
MSRP	Manufacturer’s Suggested Retail Price
ARR	Adjusted Retention Rate

1.Introduction

1.1 Research Background and Objectives

According to a report by the Environmental Protection Agency, the transportation sector accounted for 28% of U.S. greenhouse gas emissions in 2022, making it the largest contributor among all sectors[1]. Within this sector, the report also indicated that light-duty vehicles—including sedans, SUVs, and pickup trucks—are responsible for approximately 57% of emissions. In response, electric vehicles (EVs) have emerged as a key technological pathway for reducing the carbon footprint of transportation[2]. However, the widespread adoption of EVs still faces significant barriers, including high upfront costs, range anxiety, and limitations in charging infrastructure[3]. As policymakers and consumers seek to reduce emissions in this high-impact sector, it becomes increasingly important to understand the economic dynamics of EV ownership[4], particularly in the used vehicle market. In the United States, used vehicles play a dominant role: in the third quarter of 2024, 40 million of the 54.5 million light-duty vehicle sales were used vehicles[5]. During this period, used EV sales surged by 63.5% year-over-year, achieving a record market share of 1.9% [6]. This growth has been accompanied by increasing demand for more economically accessible electric models. For example, in 2023, the Tesla Model 3 accounted for 34.9% of used EV sales among vehicles aged 1 to 5 years, followed by the Model Y at 11.9% [7]. With a record 1.2 million EVs sold in the U.S. in 2023[8], and projections from Cox Automotive identifying used EVs as the fastest-growing segment in the wholesale market, the secondary EV market is poised for rapid expansion[6]. This study aims to examine the cost depreciation patterns of used EVs to inform purchasing decisions and identify optimal ownership periods. Understanding how value is retained—or lost—over time is critical to ensuring that EV adoption remains economically viable,

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[1] (Fast Facts, US EPA, 2024) https://climateprogramportal.org/wp-content/uploads/2025/02/Fast-Facts-US-Transportaton-Sector-GHG-Emissions-1990-2022.pdf
[2] (Ghosh, 2020) https://doi-org.proxy.lib.umich.edu/10.3390/en13102602
[3] (Breetz and Salon) https://doi.org/10.1016/j.enpol.2018.05.038
[4] (Woody, et al.) https://doi.org/10.1111/jiec.13463
[5] (Consumer Affairs, 2024) https://www.consumeraffairs.com/automotive/used-car-statistics.html
[6] (Recurrent Auto, 2025) https://www.recurrentauto.com/research/used-electric-vehicle-buying-report
[7] (Teslarati, 2024) https://www.teslarati.com/tesla-model-3-model-y-lead-used-ev-sales-2023
[8] (Cox Automotive, 2024) https://www.coxautoinc.com/market-insights/q4-2023-ev-sales/

particularly as the market matures and a greater number of models become available in the used inventory.

The depreciation trend of passenger vehicles is a crucial factor that buyers consider in economic assessments[9]. The depreciation of electric vehicle prices occurs because of various factors including advancements in technology, increased market competition, and improvements in manufacturing efficiency[10]. Despite the depreciation factors, one reason for the higher demand for used vehicles compared with new vehicles is the price differential between them. In the first quarter of 2024[5], the average price for a new vehicle transaction was approximately $47,000, whereas the average used vehicle transaction price was $27,000, a difference of more than 73%. This investigation centers on the question of whether electric vehicles depreciate at rates equivalent to, lower than, or higher than their internal combustion engine vehicle (ICEV) counterparts in the United States to ascertain whether the acquisition of used EVs represents a more advantageous investment based on the rate of depreciation from a buyer's perspective compared to used ICEVs.

1.2 Literature Review of Vehicle Price Depreciation

Early studies on vehicle price depreciation, such as Peles (1988)[11] and Storchmann (2004)[12], focused primarily on ICEVs. These studies employed various regression models, including linear, geometric, and polynomial functions, to analyze the relationship between the age of vehicles and residual value. Peles (1988) found that both straight-line and geometric depreciation methods provide good approximations, with true depreciation lying somewhere in between. Storchmann (2004) concluded that geometric depreciation was a better fit and observed lower depreciation rates than previous studies due to technological advancements and corrections for censored sample bias. As research progressed, more advanced multivariate regression models were developed to incorporate various factors that influence vehicle depreciation. Gilmore and Lave (2013)[13] analyzed

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[9] (Schloter, 2022) https://doi.org/10.1016/j.tranpol.2022.07.021
[10] (Motorway) https://motorway.co.uk/sell-my-car/guides/electric-car-depreciation
[11] (Peles, 1988) https://www.jstor.org/stable/42748214
[12] (Storchmann, 2004) http://dx.doi.org/10.1023/B:PORT.0000037087.10954.72
[13] (Gilmore and Lave, 2013) https://doi.org/10.1016/j.tranpol.2012.12.007

the residual values of alternative powertrains, including hybrid electric vehicles (HEVs) and diesel vehicles, and found that better fuel economies resulted in higher resale values (price of the used vehicle) compared to gasoline vehicles.

With the increasing adoption of EVs, researchers have increasingly focused on understanding resale values and depreciation patterns. Schoettle and Sivak (2018)[14] found that battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) lost their resale value more rapidly than ICEVs, but incentives helped create parity in value retention. Guo and Zhou (2019)[15] developed statistical models to quantify the effect of powertrain on residual value, using data from Edmunds and Wards Auto Data Center. They emphasized the importance of accounting for Tesla's higher-than-average adjusted retention rate (ARR[16]) and explored the potential for faster adjusted retention rate improvements in immature EV technologies. The authors concluded that Tesla Model S, with its long-range and high performance, retains values significantly better than any other vehicle model, including internal combustion engine vehicles. HEVs and PHEVs perform comparably, holding slightly less value than ICEVs, but notably more than short-range BEVs. However, short-range BEVs demonstrated the fastest improvement in 3-year adjusted retention rates among all powertrain technologies from the model years 2013–2014, with retention rates also influenced by the manufacturer's home country (e.g., the United States, Japan, and Germany).

Argonne National Laboratory (ANL) conducted two comprehensive studies in 2021 and 2022 on the total cost of ownership for various vehicle powertrains and size classes. The 2021 ANL study highlighted notable differences in depreciation and residual values across powertrain types[17]. In this analysis, both BEVs and PHEVs initially exhibited higher 3-year ARR[16] compared to HEVs and ICEVs, with BEVs showing only marginally higher ARR. Unlike earlier findings by Guo and Zhou (2019)[15], who reported lower residual values for BEVs and PHEVs, this study indicates a shift, with these alternative powertrains maintaining higher residual values than their conventional

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[14] (Schoettle and Sivak, 2018) https://trid-trb-org.proxy.lib.umich.edu/View/1508113

[15] (Guo and Zhou, 2019) https://doi.org/10.1016/j.enpol.2018.10.023

[16] Adjusted Retention Rate (ARR) accounts for the impact of federal tax incentives on resale value by adjusting the depreciation calculation relative to the post-incentive purchase price (ANL, 2022).

[17] (ANL, 2021) https://publications.anl.gov/anlpubs/2021/05/167399.pdf

counterparts. Factors contributing to this trend include advancements in BEV performance, such as an increased electric range and improved energy efficiency, making them more competitive with traditional vehicles.

The 2022 ANL study[18] examined the evolution of residual values over time using two methods to analyze depreciation: (1) a time-series method, which fits an exponential function to the ARR data for a single model year over multiple calendar years, and (2) a snapshot method, which fits an exponential function to the ARR data across multiple model years within a single calendar year. The study, based on True Market Value (TMV) transaction data from Edmunds, found that more mature powertrain technologies, such as ICEVs and HEVs, exhibited more consistent 3-year ARR over time, whereas newer technologies, such as BEVs and PHEVs, demonstrated greater variability. Regression analysis indicated that powertrain type, market segment, size class, and automaker country were statistically significant in predicting the 3-year ARR.

Schloter (2022)[9] performed a cross-country analysis using data from multiple sources, including Autoscout24, Bybil, and Edmunds, employing a multivariate regression approach. This empirical study compares the depreciation patterns of EVs and ICEVs across multiple countries, providing insights into regional variations in EV depreciation. The key findings of this study suggest that vehicles generally have a degressive (decreasing overtime) depreciation relationship, but EVs have a substantially higher depreciation rate of 1.16% per month (13.9% per annum) than gasoline vehicles at 0.87% per month (10.4% per annum). The authors concluded that the higher depreciation of EVs compared to gasoline vehicles is typical for nascent technologies, but this gap may decrease as the EV market matures. Roberson et al. (2024)[19] developed an exponential decay model to estimate EV price retention rates. Their study found that BEVs and PHEVs generally depreciate faster than conventional ICEVs, though this gap is narrowing for newer BEV models with longer ranges. Notably, Tesla BEVs showed the highest initial value retention but also experienced sharper depreciation in recent model years, reflecting changing market dynamics. Table 1.1 summarizes some of the key

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[18] (ANL, 2022) https://publications.anl.gov/anlpubs/2022/07/176711.pdf
[19] (Roberson et al., 2024) https://iopscience.iop.org/article/10.1088/1748-9326/ad3fce

literature in the field of vehicle price depreciation, their findings, and the models analyzed.

Table 1.1: Highlights of previous studies on vehicle price depreciation, their findings, and models developed.

Author	**Key Findings**	**Model**
Peles (1988)	Both straight-line and geometric depreciation are good approximations for ICEV depreciation.	Residual asset value function regression
Storchmann (2004)	Geometric depreciation is a better approximation than linear. Annual depreciation rates were lower than previous studies, due to technological change and correction for sample bias.	Third-order polynomial regression of price vs. age
Gilmore and Lave (2013)	Better fuel economies (HEV, diesel) resulted in higher resale values compared to conventional gasoline vehicles.	Regression model for sales price vs. mileage
Wu et al. (2015)	Used Linz et al. (2003) method to approximate EV values due to lack of empirical EV resale data.	Hedonic price regression
Schoettle and Sivak (2018)	BEVs and PHEVs lost resale value quicker than ICEVs without incentives. With incentives, PHEVs had similar resale value retention as ICEVs.	N/A (empirical data analysis)
Guo and Zhou (2019)	Developed statistical models to quantify the effect of powertrain on resale value. Excluding Tesla, BEVs had lower adjusted retention rates than ICEVs.	Adjusted retention rate regression, binary variable regression
ANL (2021)	Key findings: PHEV and EV increasingly retain higher residual rates over time relative to ICEV. Provided retention rate curves by vehicle class and powertrain.	Exponential regression models
ANL (2022)	Advancements in EV tech have led to plug-in vehicles exhibiting depreciation curves similar to conventional vehicles. Analyzed snapshot and time series data.	Adjusted retention rate calculation, regression analysis
Schloter (2022)	Multivariate regression analysis showed higher depreciation rates for BEVs compared to ICEVs across 5 countries.	Multiple regression (hedonic pricing method)

Roberson (2024)	While EVs depreciate faster than ICEVs, newer BEVs with longer ranges show improved retention, and Tesla BEVs depreciate slower due to brand premium, and federal subsidies reduce resale prices.	Multiple linear regression model with interaction terms

Our study offers a novel contribution to the existing literature on vehicle price depreciation by providing a comprehensive empirical analysis of used vehicle depreciation trends in the United States. While prior studies, such as those by Guo and Zhou (2019) and Schloter (2022), have explored vehicle depreciation patterns across various powertrain types and regions, the current research uniquely combines a more granular dataset with an expanded scope of analysis. Additionally, while the ANL (2022) study employed time-series and snapshot methods to examine residual value trends nationwide, our study uniquely integrated regression analysis to assess the combined influence of powertrain type, vehicle class, age, and mileage, providing a more detailed understanding of depreciation patterns within distinct regional and demographic contexts. In addition, unlike the ANL (2022) study that relies on TMV data reflecting actual transaction prices across the entire U.S. market, our dataset is web-scraped from Craigslist and does not capture the final transaction prices. These differences in data sources, geographic scope, and pricing representation may lead to variations in the observed depreciation trends and the interpretation of factors influencing residual values.

In our study we examined four powertrain types: BEVs, HEVs, PHEVs, and ICEVs. Moreover, the analysis incorporates three vehicle classes, SUVs, sedans, and pickup trucks, offering insights into depreciation patterns across diverse vehicle segments, an area that has received limited attention in the existing literature. This multidimensional approach allows for a nuanced understanding of how powertrain technology and vehicle class jointly influence depreciation rates. This study's comprehensive scope, multi-factor analysis, and focus on recent data make it uniquely positioned to address the critical gaps in existing literature. By doing so, it advances the understanding of depreciation trends in the U.S. using the vehicle market and informs both academic discourse and practical decision-making for consumers, policymakers, and industry stakeholders.

2. Method

2.1 Data Collection

Web scraping tools were utilized to collect publicly accessible data from the e-commerce platform Craigslist. These tools employ code scripts to automate the process of loading, interacting, and collecting data from webpages. The code procedure consisted of two steps. Initially, the "link collection step" involved querying the e-commerce platform for vehicles with search parameters to obtain the links associated with listings on that day. The search parameters consisted of a zip code and search radius. Subsequently, each of the listed links gathered in the first step was loaded, and relevant data fields, such as mileage, list price, and powertrain, were collected.

This web scraping process was executed once daily for a total period of one year (December 2023 to December 2024) and collected over 3.9 million data points were collected. The collected dataset included crucial information pertaining to vehicles, such as vehicle class, model, powertrain, model year, mileage, and listing price, among other pertinent parameters. We used the listed price as an analog for resale value. It is important to note that the prices used in this analysis reflect seller-listed prices on Craigslist at the time of data collection, rather than the actual transaction price. Additionally, we obtained MSRP (Manufacturer's Suggested Retail Price) data for vehicles in our dataset by downloading information from carsheet.io[20] using a web scraping approach. Vehicles were matched based on their make, model, year, and trim, ensuring that the price data corresponded accurately to each listing in our study. Where multiple MSRPs were listed for the same vehicle (e.g., due to multiple available trims), we used the mean of those values.

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[20] (https://carsheet.io/) Carsheet.io is a tool for sorting, filtering, and comparing cars.

2.2 Data Cleaning

To ensure data quality and reliability, we implemented a comprehensive cleaning procedure. First, we addressed missing values (NAs) and removed duplicate vehicle listings to maintain data integrity. Currency standardization was performed by excluding non-USD listings and retaining only USD-denominated prices. We also removed vehicles with "Salvage" titles as these represent atypical depreciation patterns due to prior significant damage. Our analysis focused on vehicles with prices ranging from $1,000 to $150,000 and model years between 2010 and 2023, providing a contemporary yet comprehensive view of the market. Data validation included checking for correct labeling to avoid user input errors. We also focused on four kinds of fuel types- electric, gasoline, hybrid electric, and plug-in hybrid electric, and three types of vehicle classes- sedans, SUVs, and pick-up trucks. After these cleaning procedures, our analysis was performed on a dataset of approximately 150,000 vehicle entries.

2.3 Geographic Location

We investigated 17 cities in the United States: Atlanta, Boston, Chicago, Cleveland, Dallas, Denver, Detroit, Houston, Los Angeles, Miami, Minneapolis, New York City, Philadelphia, Phoenix, San Francisco, Seattle, and Washington D.C. The city selection aimed to represent various geographic regions, climates, and demographic profiles, while including many of the largest vehicle markets in the U.S. Data were collected within a 50-mile radius from the central point of each city to ensure a localized and contextually relevant dataset. Location was not included as a variable in the base case but was explored separately in an additional regression analysis. To assess the impact of winter road treatment on vehicle depreciation, a subset regression analysis was conducted comparing retention rates between regions that frequently salt their roads and regions that do not (see Appendix C, Table C.1). This approach allowed us to isolate the effect of road salting on long-term vehicle value.

2.4 Modeling Retention Rate

Previous studies on vehicle depreciation and residual value estimation have employed various modeling approaches to quantify how vehicle prices decline over time. Common methodologies include linear regression, log-linear models, and machine learning techniques. Prior research, such as Schloter (2022) and Roberson et al. (2024), has demonstrated that vehicle retention rates are best captured using exponential decay models, where depreciation follows a nonlinear pattern over time. Schloter (2022) proposed a fundamental model that expressed the natural logarithm of the resale value of the vehicle as a function of cumulative mileage and vehicle age. Eq. 1 represents their model that captured the basic mechanics of depreciation.

$$\log(\text{Resale Value}) = \beta 0 + \beta 1(\text{Age}) + \beta 2(\text{Mileage per Month}) + \beta 3(\log(\text{Average MSRP})) + \beta 4(\text{Fuel}) + \beta 5(\text{Vehicle Type}) + \beta 6(\text{Seller Type}) \quad \ldots\ldots\ldots\ldots \text{(Eq. 1)}$$

Expanding on this foundation, Roberson et al. (2024) introduced a more nuanced model that incorporated interactions between vehicle age and several categorical variables. By including interaction terms, Roberson et al. captured how the effect of age on depreciation varies with fuel type, Tesla ownership (as a specific case study), and initial vehicle price. Their model is expressed in Eq. 2.

$$\log(\text{Retention Rate}) = \beta 0 + \beta 1(\text{Age} * \text{Fuel}) + \beta 2(\text{Age} * \text{Tesla}) + \beta 3(\text{Mileage per Year}) + \beta 4(\text{Age} * \log(\text{Average MSRP})) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Eq. 2)}$$

We tested regression models based on these previous approaches and made refinements to improve fit using our dataset. Building upon these insights, our model, in Eq. 3, integrates elements from both approaches while focusing specifically on the logarithm of the retention rate as our dependent variable and interactions between age and categorical variables (fuel type, vehicle class, and seller type) while also incorporating the interaction between age and the logarithm of MSRP:

$$\log(\text{Retention Rate}) = \beta_0 + \beta_1(\text{Miles per Year}) + \beta_2(\text{Age} * \text{Fuel Type}) + \beta_3(\text{Age} * \text{Vehicle Class}) + \beta_4(\text{Age} * \text{Seller Type}) + \beta_5(\text{Age} * \log(\text{Average MSRP})) \;\ldots\ldots\; (\text{Eq. } 3)$$

Where,

$$\text{Retention Rate} = (\text{Listing Price} / \text{MSRP})$$

Key Variables:

- Age: The age of the vehicle in years
- Fuel Type: Categorical variable with levels such as Diesel, Electric, Gas, Hybrid, and PHEV, with Diesel as a baseline category
- Vehicle Type: Categorical variable representing vehicle classes (such as Sedan, Pickup Truck, SUV) with a baseline of Sedan
- Seller Type: Binary variable indicating whether the vehicle was sold by the owner or a dealership
- MSRP: Manufacturer's Suggested Retail Price

2.5 Tesla vs non-Tesla

To assess differences in price depreciation between Tesla and non-Tesla (vehicles that are not manufactured by Tesla) BEVs, we incorporated a binary variable, *is_tesla*, where non-Tesla vehicles served as the baseline. This analysis was conducted to understand whether Tesla vehicles retain their value differently compared to other BEV brands, given their brand recognition, technological differentiation, and potential demand variations in the used vehicle market.

3. Results and Discussion

To analyze the depreciation patterns of used electric vehicles, we compared different regression models, each designed to capture different aspects of price retention dynamics. Eq. 3 serves as a baseline regression, estimating vehicle price as a function of fundamental factors such as age, mileage, fuel type, vehicle class. We then analyzed brand-specific effects, incorporating a Tesla indicator variable and interaction terms to examine whether Tesla vehicles exhibit distinct depreciation trends compared to other EVs. We further deployed the model to examine city-level effects. We also validated our model by comparing it with the Roberson et al. (2024) and Schloter (2022) models. By comparing across models, we aim to isolate key drivers of price retention and assess how depreciation patterns vary across different EV segments and market conditions.

3.1 Model Analysis

Our model, as seen in Eq. 3, estimates vehicle price retention rate as a function of key attributes (age, mileage, fuel type, vehicle class, and geographic location, average MSRP, seller type). The regression model employed an ordinary least squares (OLS) approach to examine the logarithm of the retention rate as a function of the relevant independent variables. The model incorporated interaction terms between age and fuel type, age and vehicle type, age and seller type, and age and logarithm of the average MSRP to capture differential depreciation trends across these categorical variables. The model yielded an R-squared (R^2) value of 0.603, indicating that approximately 60.3% of the variance in the logarithmic of the retention rate is explained by the independent variables included in the model. Table 3.1 summarizes model coefficients.

Table 3.1: Coefficient table of the retention rate model (Eq.3).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.203e+00	5.781e-02	38.117	<2e-16***
Age	-1.347e-01	6.596e-03	20.426	<2e-16***
fuelhybrid	8.208e-02	1.001e-02	8.197	2.48e-16***
fuelPHEV	4.541e-02	4.350e-02	1.044	0.2966
fuelelectric	-1.762e-01	1.154e-02	-15.272	<2e-16***
typepickup	1.259e-01	7.432e-03	16.940	<2e-16***
typeSUV	2.723e-02	4.456e-03	6.111	9.90e-10***
seller_typeowner	-1.463e-02	6.044e-03	-2.421	0.0155*
odometer_by_age	-2.799e-05	1.614e-07	-173.366	<2e-16 ***
log(MSRP_avg)	-1.776e-01	5.563e-03	-31.916	<2e-16 ***
Age:fuelhybrid	8.187e-04	1.154e-03	0.710	0.4780
Age:fuelPHEV	2.322e-03	5.779e-03	0.402	0.6878
Age:fuelelectric	9.448e-03	1.924e-03	4.910	9.11e-07***
Age:typepickup	2.954e-02	8.699e-04	33.957	<2e-16 ***
Age:typeSUV	2.062e-03	5.072e-04	4.066	4.79e-05***
Age:seller_typeowner	-1.168e-02	6.406e-04	-18.226	<2e-16 ***
Age:log(MSRP_avg)	-2.337e-02	6.386e-04	-36.589	<2e-16***

Examining the coefficient estimates in Table 3.1, BEVs demonstrated lower retention rates compared to gasoline vehicles (reference category). HEVs also showed statistically significant differences from ICEVs, indicating that these alternative gasoline powertrains (ICEV vs HEV) influence vehicle depreciation patterns differently. The vehicle-type coefficients revealed significant variations in the depreciation trends. Pickup trucks and SUVs exhibited higher retention rates compared to the reference category Sedans. Additionally, seller type played a role in depreciation, with owner-sold vehicles exhibiting lower retention rate than vehicles sold by dealerships. Mileage per year (which is the *odometer_by_age* variable in our model) negatively correlated with retention rate, implying that higher mileage per year accelerates depreciation.

The interaction effects, as seen in Table 3.1, revealed how depreciation trends differ across vehicle segments. The interaction terms between vehicle age and vehicle type indicated that pickups and SUVs experience relatively slower depreciation than sedans. The negative coefficient for the interaction between age and seller suggested that owner-sold vehicles depreciate at a slightly faster rate than dealer-sold vehicles. Interaction between age and natural logarithmic of the average MSRP indicated that vehicles with higher initial price points tend to experience steeper depreciation rates over time. Figure 3.1 shows the relation between average retention rate and mileage for a random sample of 1000 vehicles for each powertrain except for PHEVs, as PHEV has a very small number (232) of entries on our dataset.

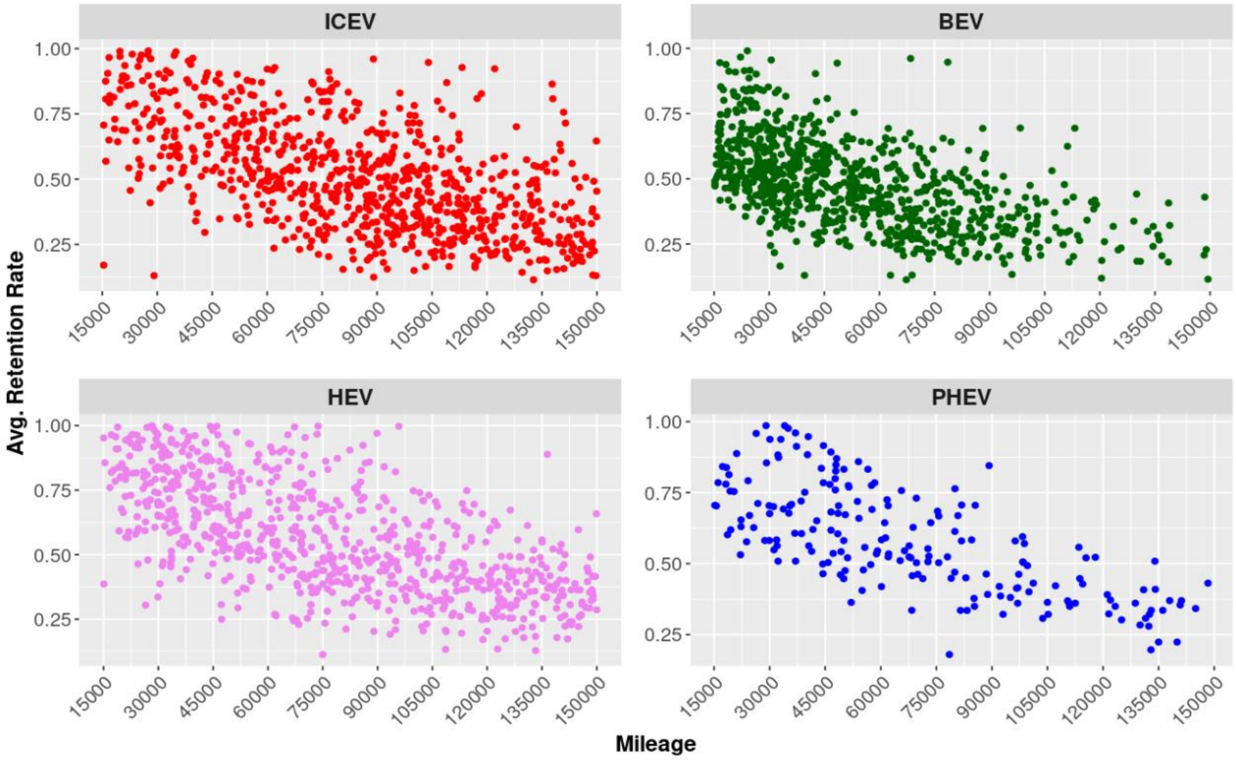

Fig. 3.1: Retention rate vs Mileage across different powertrains for a sample of 1000 ICEVs, 1000 EVs, 1000 HEVs, and all PHEVs in our dataset.

Figure 3.1 reveals that across all powertrains a negative correlation is observed between mileage and retention rate, indicating that vehicle value generally decreases as mileage increases. Among the four categories, HEVs exhibit the highest average retention rates across the mileage spectrum, suggesting slower depreciation relative to other powertrain types. In contrast, BEVs show a steeper decline in retention rate with increasing mileage, implying more rapid depreciation, particularly beyond 60,000 miles. ICEVs demonstrate a moderate depreciation pattern, while PHEVs also exhibit better retention rates than BEVs but there is greater variability in the data due to the smaller sample size. This visual analysis highlights differences in mileage sensitivity of depreciation across fuel types, with potential implications for total cost of ownership, consumer preferences, and secondary market dynamics.

3.1.1 Depreciation Curves Across Different Types of Powertrains

To isolate the effect of powertrain type on depreciation trends, we simulated depreciation curves across different powertrain types, including BEVs, PHEVs, HEVs, and ICEVs. The findings revealed several key trends in vehicle depreciation. BEVs experience rapid initial depreciation, consistent with previous research (Roberson et al., 2024), likely due to consumer apprehensions regarding battery degradation and technological obsolescence. PHEVs and HEVs demonstrate the highest initial retention and the slowest depreciation, with HEVs slightly outperforming PHEVs throughout most of the vehicle lifespan. ICEVs show moderate depreciation patterns, while BEVs exhibit the steepest decline in value retention. By year 5.5 approximately, electric vehicles dip below the 50% retention threshold, earlier than other powertrains. This trend underscores the relatively rapid loss of value in electric sedans, possibly due to market uncertainties and battery aging, while HEV and PHEV sedans retain their value longer, potentially due to broader consumer acceptance and established reliability[21]. Figure 3.2 provides a visual representation of how resale value evolved over time across different fuel technologies for sedans.

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[21] (Detroit Free Press, 2023) https://www.freep.com/story/money/cars/mark-phelan/2023/11/29/consumer-reports-reliability-survey-electric-vehicles-hybrids/71723557007/

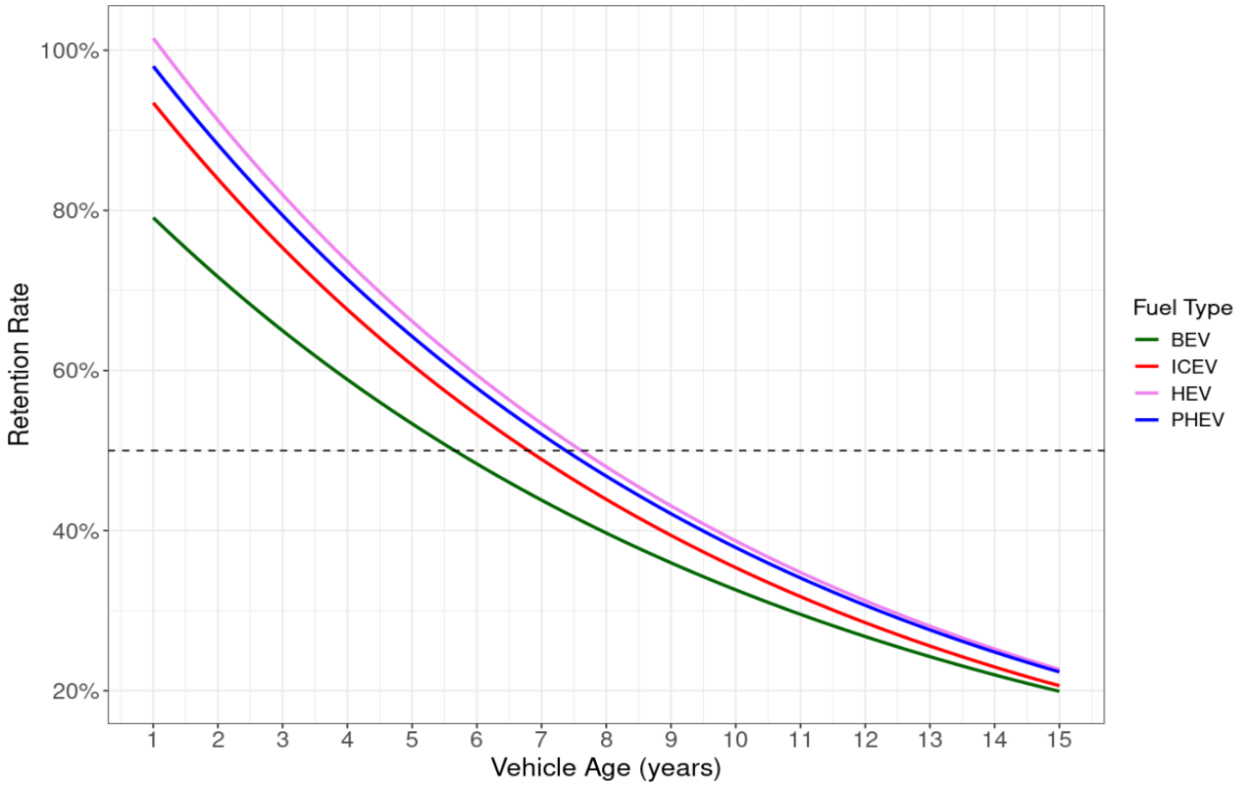

Fig. 3.2 Depreciation pattern of across different powertrain over a 15-year horizon. The horizontal dashed line signifies a 50% retention rate milestone.

3.1.2 Depreciation Across Different Vehicle Classes

Figure 3.3 displays the price depreciation curves across three vehicle classes segmented by the four fuel types analyzed in our dataset. Across all three vehicle classes, retention rate declines with age, following a nonlinear depreciation pattern. BEVs consistently exhibit the steepest depreciation, reaching lower retention rates at earlier ages compared to other powertrains. In contrast, HEVs and PHEVs retain value better over time, particularly in the sedan and SUV segments. ICEVs demonstrate intermediate depreciation behavior, generally retaining more value than BEVs but less than hybrid variants. Notably, this pattern holds across vehicle classes, though pickups tend to retain their value slightly better across all fuel types, especially in early years. These findings underscore the influence of powertrain type on depreciation behavior and suggest that HEVs and PHEVs retain superior long-term value, while BEVs continue to experience more rapid depreciation across all vehicle classes.

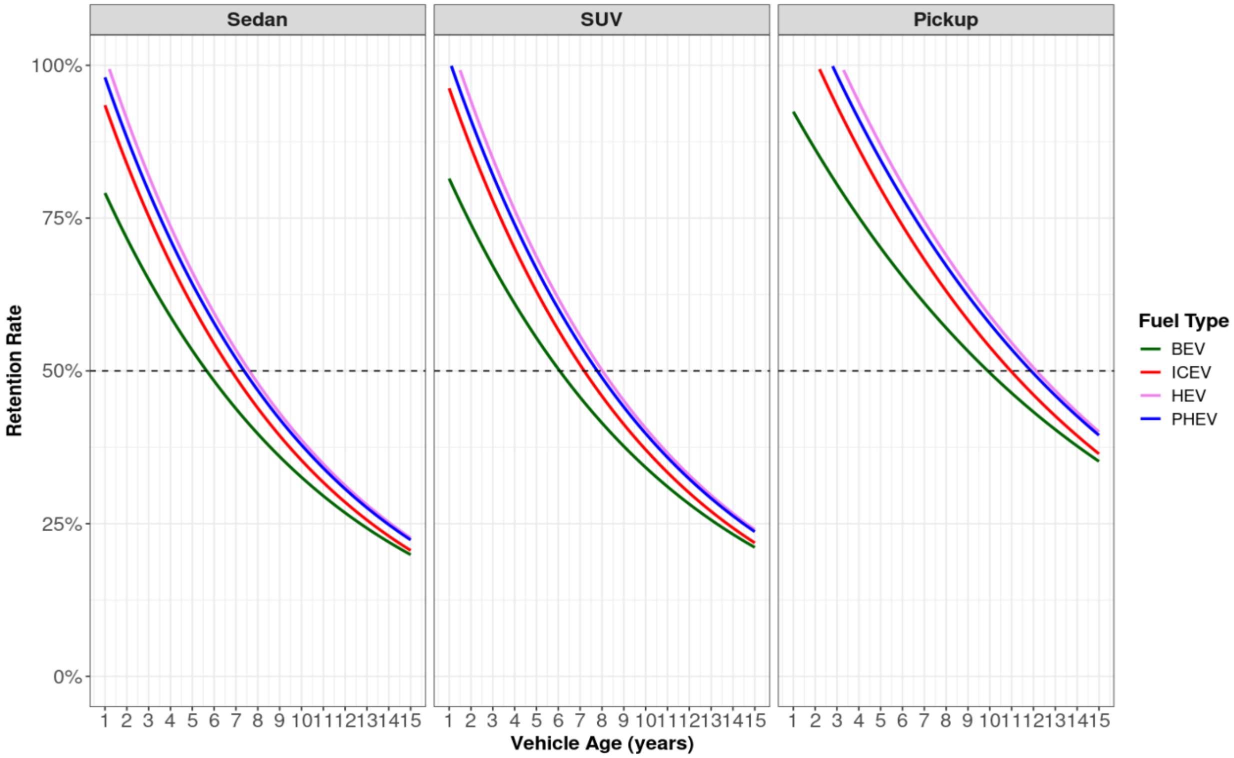

Fig. 3.3 Price depreciation pattern for vehicles of different classes and fuel types. The y-axis represents the retention rate (the ratio of current price to original MSRP), while the x-axis indicates vehicle age in years, spanning up to 15 years. A horizontal gray dashed line at the 50% retention rate serves as a reference threshold.

3.2 Location-Based Depreciation Trends

To examine the influence of geographic location on vehicle depreciation, city-level fixed effects were incorporated into the regression model with Chicago serving as the reference category. The results indicate that depreciation rates exhibit significant variation across metropolitan areas, highlighting the role of regional market dynamics in shaping used vehicle values[22]. These variations also suggest that local economic conditions, infrastructure, and policy incentives may influence how different vehicle types retain their value over time[23]. Figure 3.4 shows regional variation in depreciation in three

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[22] (Car and Driver, 2023) https://www.caranddriver.com/auto-loans/a32766551/best-state-to-buy-a-car/
[23] (Clinton and Steinberg, 2019) https://doi.org/10.1016/j.jeem.2019.102255

selected cities. Prior research has shown that vehicle ownership costs, including depreciation, vary widely by region[24]. Breetz and Salon (2018) analyzed the cost differences in owning conventional, hybrid, and electric vehicles across 14 U.S. cities, attributing regional disparities in depreciation rates to factors such as state and local regulations, fuel costs, and consumer demand. Similarly, Woody et al. (2024) found that EVs are more cost competitive in regions with high gasoline prices, low electricity costs, strong policy incentives, and with greater home charging usage. The findings from these studies reinforce the importance of regional variability across different fuel types (BEV and ICEV) observed in this research, as can be seen in Figure A.1 and A.2 in Appendix section A.

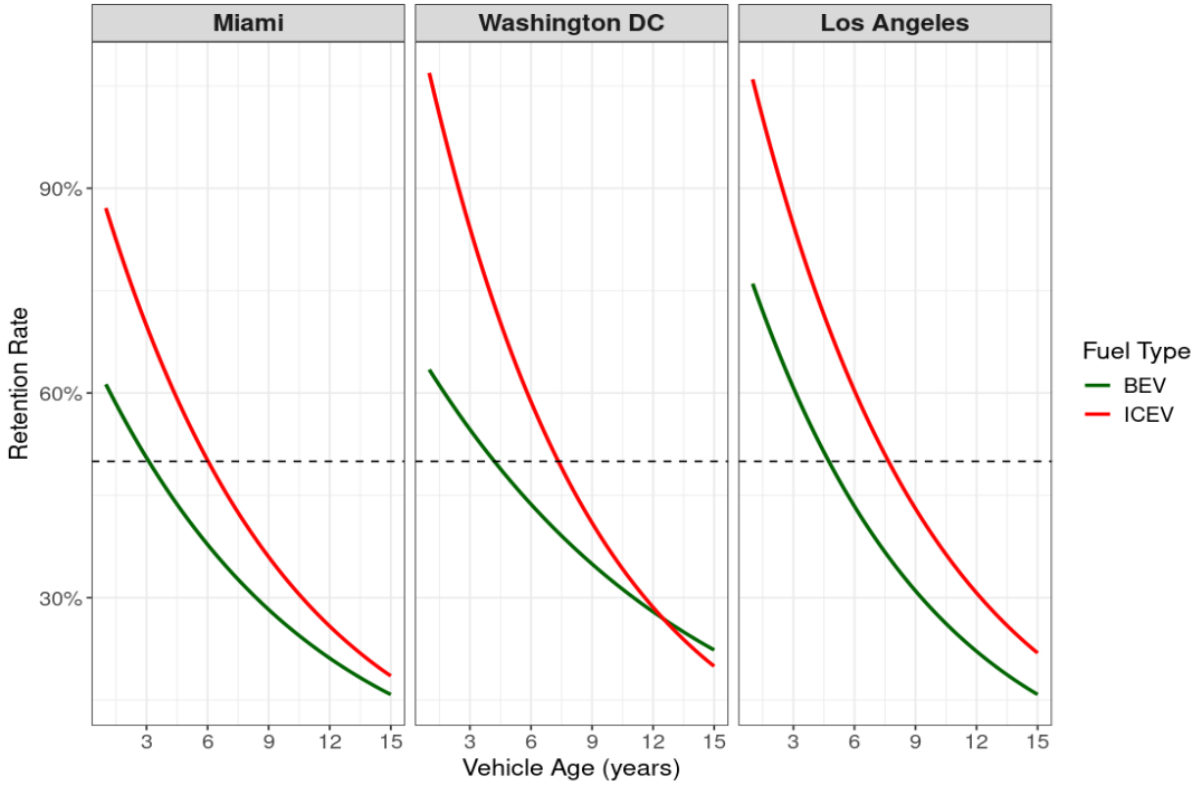

Fig. 3.4 Differences in vehicle value retention rate over a 15-year period in three selected cities. A horizontal gray dashed line at the 50% retention rate serves as a reference threshold.

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[24] (Thakuriah and Liao, 2005) https://doi-org.proxy.lib.umich.edu/10.1177/0361198105192600101

3.2.1 Cities with Lower Depreciation

Several cities demonstrate statistically significant positive coefficients (Table A.1, Appendix A), indicating that vehicles in these markets retain their value better than those in our baseline city Chicago. These cities include:

- Boston (+0.083, $p < 0.0001$)
- Atlanta (+0.069, $p < 0.0001$)
- Dallas (+0.069, $p < 0.0001$)
- Minneapolis (+0.045, $p < 0.0001$)
- Washington, D.C. (+0.037, $p < 0.01$)
- Denver (+0.025, $p < 0.0001$)

The positive coefficients suggest that vehicles in these regions experience slower depreciation rates, potentially due to higher demand for used vehicles, regional economic factors, or market supply constraints.

3.2.2 Cities with Higher Depreciation

Conversely, several cities exhibit significantly negative coefficients, indicating that vehicles in these markets depreciate more rapidly than those in our baseline city Chicago.

- Miami (-0.169, $p < 0.0001$)
- New York (-0.071, $p < 0.0001$)
- Detroit (-0.064, $p < 0.0001$)

Among these, Miami exhibited the steepest depreciation trend. The significantly negative coefficient suggests that vehicles in Miami retain substantially less value over time than those in Chicago. Though we did not investigate causation, potential causes may include increased exposure to environmental factors such as humidity and flooding risk, or a stronger preference for new vehicles in the local market. New York and Detroit also showed accelerated depreciation, which may stem from a combination of high urban vehicle supply, and lower long-term demand for used vehicles in these regions.

3.3 Effect of Winter Road Treatment on Vehicle Price Depreciation

We modified our model (Eq. 3) to capture the effects of road treatment during the winter. Typically, roads are frequently treated with ice salt in winter when snowy conditions are encountered. In Eq. 4, we introduced a binary variable named *Salting* to account for road salting effect on vehicle price retention.

$$\log(\text{Retention Rate}) = \beta 0 + \beta 1\,(\text{Age} * \text{fuel} * \text{Salting}) + \beta 2\,(\text{Age} * \text{type} * \text{Salting}) + \beta 3\,(\text{Miles per Year}) + \beta 4(\text{Age} * \log(\text{MSRP\_avg})) + \beta 5\,(\text{Seller\_type}) \quad \ldots\ldots\ldots\ldots\ldots \text{(Eq. 4)}$$

The analysis reveals that road salting has a significant impact on vehicle depreciation, as evidenced by the positive coefficient for salting ($\beta = +0.059$, $p < 0.001$, see Table B.1 in Appendix section B), indicating that vehicles in salted regions exhibit almost 6% higher initial retention rate than those in non-salted regions. This counterintuitive result may reflect regional market dynamics, such as a higher demand for corrosion-resistant vehicles (e.g., pickups/SUVs) in cold climates. However, this short-term advantage diminishes with age owing to interaction effects. Figure 3.5 compares the retention rates of sedans by fuel type in regions with and without road salt usage.

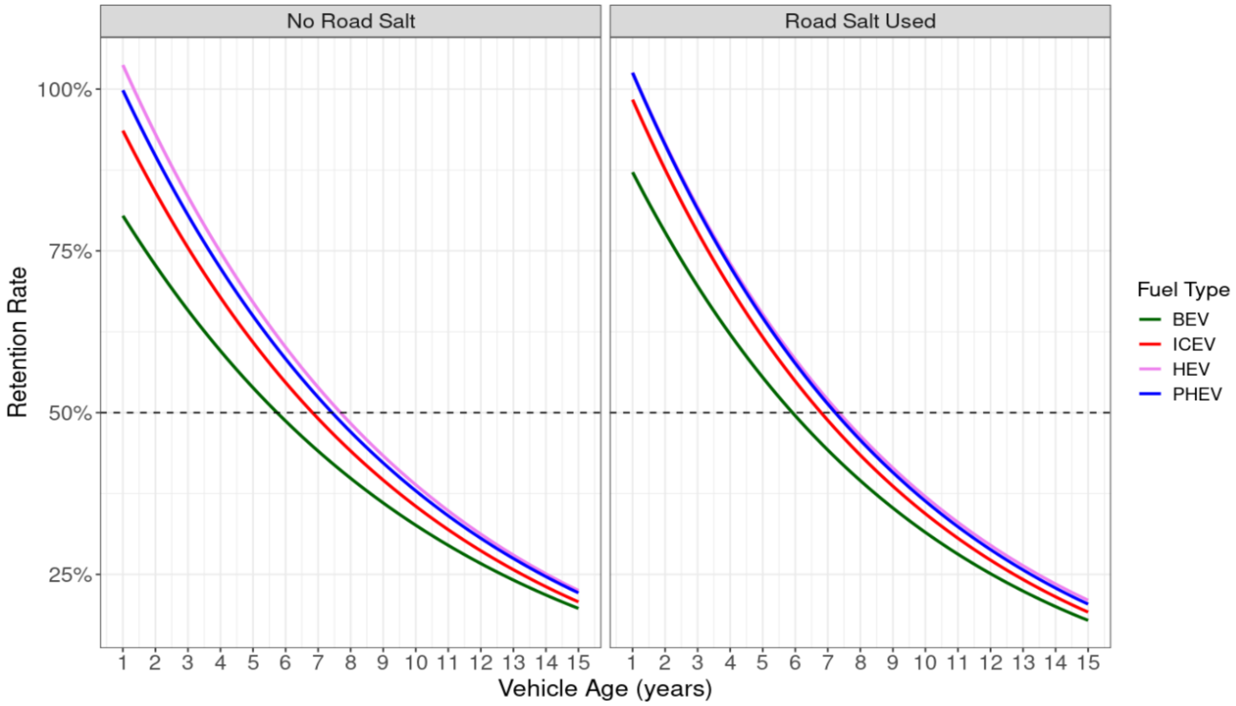

Fig. 3.5: Impact of road salt on sedan depreciation by fuel type, over a period of 15 years. The left panel shows depreciation trends in areas without road salt, while the right panel reflects areas where road salt is commonly used. A horizontal gray dashed line at the 50% retention rate serves as a reference threshold.

3.4 Tesla vs Other BEVs

To assess the differential depreciation patterns between Tesla and non-Tesla battery electric vehicles, we modified our regression model to incorporate a binary variable *is_tesla*. Eq. 5 shows the specification used to model the log of the retention rate to evaluate depreciation pattern in Tesla vs non-Tesla BEVs.

$$\log(\text{Retention Rate}) = \beta 0 + \beta 1(\text{is\_tesla} * \text{Age}) + \beta 2(\text{Age} * \text{type}) + \beta 3(\text{Age} * \text{seller\_type}) + \beta 4(\text{Mileage per Year}) + \beta 5(\text{Age} * \log(\text{MSRP\_avg})) \ldots\ldots\ldots \text{(Eq. 5)}$$

In Eq. 5, non-Tesla and sedan type vehicles serve as the reference category. The model explains approximately 68.6% of the variation in retention rates. Table 3.2 presents a statistical summary of the model analyzed.

Table 3.2: Statistical results from a regression analysis to compare depreciation patterns in Tesla vs other (non-Tesla) BEV brands.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.723e+00	2.985e-01	5.771	8.82e-09 ***
is_tesla	9.617e-02	2.294e-02	4.192	2.85e-05 ***
Age	-5.462e-02	4.527e-02	-1.206	0.22775
typeSUV	5.630e-02	2.184e-02	2.577	0.01001 *
seller_typeowner	7.033e-02	2.344e-02	3.001	0.00272 **
odometer_by_age	-1.539e-05	8.448e-07	-18.221	<2e-16 ***
log(MSRP_avg)	-1.684e-01	2.749e-02	-6.128	1.03e-09 ***
is_tesla:Age	-9.614e-03	3.995e-03	-2.406	0.01618 *
Age:typeSUV	-1.818e-02	3.614e-03	-5.030	5.24e-07 ***
Age:seller_typeowner	-1.748e-02	3.734e-03	-4.681	3.01e-06 ***
Age:log(MSRP_avg)	-3.625e-03	4.163e-03	-0.871	0.38389

The analysis of Tesla vehicle depreciation reveals intriguing patterns in the battery electric vehicle market. Tesla vehicles initially demonstrate a higher retention rate than comparable non-Tesla BEVs. This substantial initial advantage is highly statistically significant (p = 2.85e-05), indicating a strong consumer preference for Tesla's brand and technology at the point of purchase. However, the depreciation trajectory for Tesla vehicles diverges from their non-Tesla counterparts over time. The main effect of vehicle age is negative but not statistically significant. However, the interaction between Tesla status and age is negative and statistically significant, implying that Tesla vehicles experience a slightly steeper depreciation trajectory with increasing age relative to their non-Tesla counterparts. This pattern of depreciation rate also suggests that Tesla's initial value advantage may diminish more rapidly over time. Figure 3.6 shows depreciation curves across battery electric sedans and battery electric SUVs, highlighting their differences across Tesla vs non-Tesla manufacturers. The convergence of Tesla and non-Tesla values occurs at approximately 10 years for both SUVs and sedans. Initially, both Tesla sedans and SUVs exhibit a higher retention rate compared to their non-Tesla counterparts, demonstrating a "Tesla premium" in the early years of ownership. However, this premium is gradually eroded as Tesla vehicles depreciate at a faster rate than non-Tesla vehicles over time. The finding—that Tesla vehicles initially retain value better but depreciate more steeply than other BEVs over time—was affirmed in conversation with Jimmy Douglas, CEO of Plug, who noted that this pattern aligns with market dynamics observed across wholesale remarketing platforms (personal communication, January 2025).

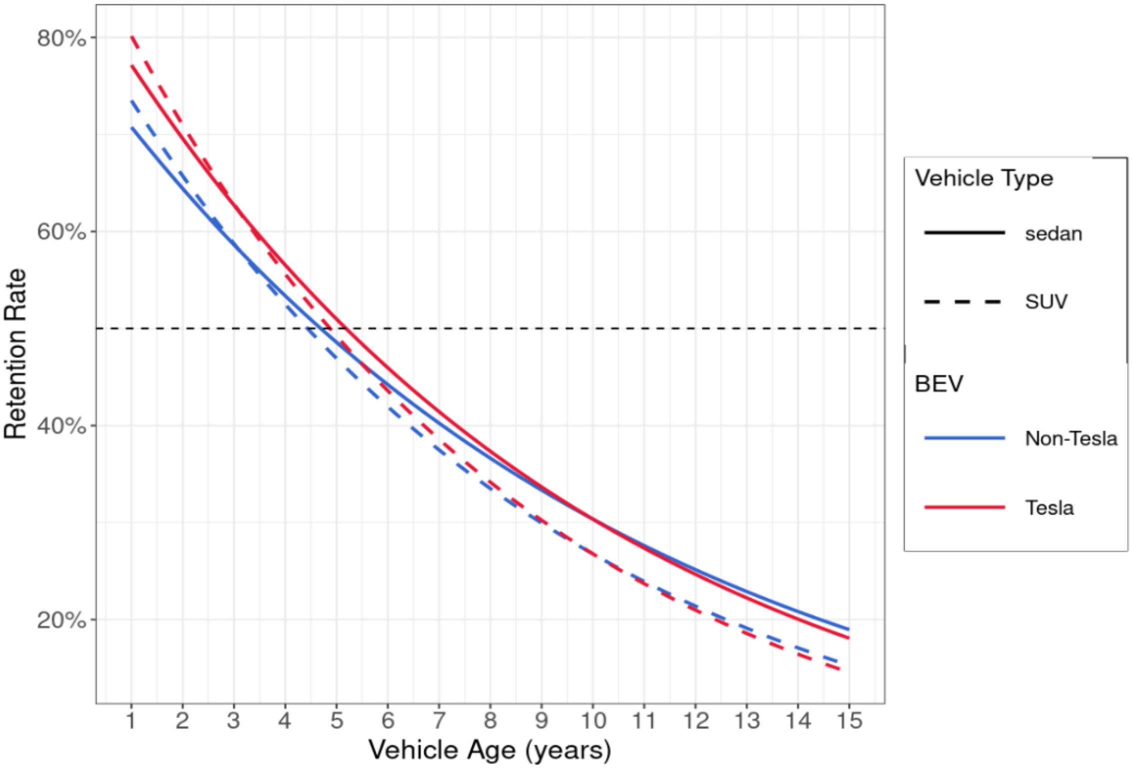

Fig. 3.6: Depreciation curves showing insights into the comparative value retention of Tesla and non-Tesla BEVs, particularly sedans and SUVs. A horizontal black dashed line at the 50% retention rate serves as a reference threshold.

In summary, Tesla electric vehicles command a significant price premium when new, but this advantage gradually erodes as vehicles age, with Tesla vehicles depreciating slightly faster than their non-Tesla counterparts. After approximately 10 years, the Tesla premium disappears entirely. For consumers, this suggests that Tesla vehicles may be better short-term investments (1-5 years), while non-Tesla electric vehicles may be better long-term value propositions (10+ years).

3.5 Comparison with Schloter (2022) and Roberson (2024) Models

3.5.1 Schloter (2022) Model

In this analysis, we compared the original model proposed by Schloter (2022) with a modified version tailored to incorporate "*mileage per year*" instead of "*mileage per month*." We also modeled the natural logarithm of *Retention Rate* instead of *Resale Value*. Schloter's original model is specified in Eq. 1, the modification we implemented is shown in Eq. 6. We then utilized our dataset to implement the model.

$$\log(\text{Retention Rate}) = \beta 0 + \beta 1(\text{Age}) + \beta 2(\text{Mileage per Month}) + \beta 3(\log(\text{Average MSRP})) + \beta 4(\text{Fuel}) + \beta 5(\text{Vehicle Type}) + \beta 6(\text{Seller Type}) \ldots\ldots\ldots\ldots\ldots\ldots \text{(Eq. 6)}$$

The visualization in Figure 3.7 reveals that both vehicle types experience significant depreciation over time, following a generally similar trajectory. Gas sedans consistently maintain a slightly higher retention value compared to their electric counterparts across most of the 15-year period. In the first year of ownership, vehicles generally retained between 85% and 92% of their original value, with gasoline sedans exhibiting higher initial value retention. Both vehicle types converge around the 50% retention threshold between years six and seven, suggesting that, on average, sedans lose half of their value within this period. By year fifteen, the depreciation becomes more pronounced, with both gas and electric sedans retaining only approximately 20% of their initial market value.

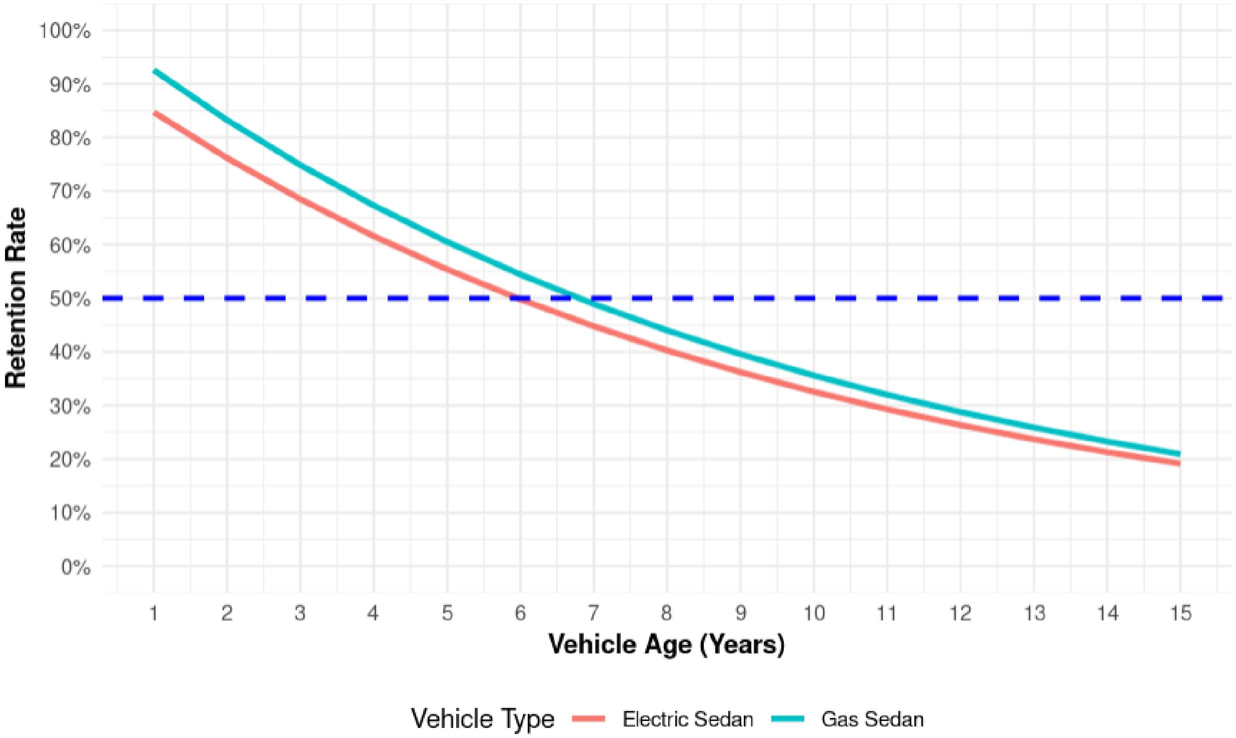

Fig. 3.7: The Schloter (2022) model comparing gas versus electric sedans with two distinct depreciation curves. The plot illustrates the retention rate (y-axis, ranging from 0% to 100%) as a function of vehicle age in years (x-axis, spanning 1 to 15 years). A horizontal blue dashed line at the 50% retention rate serves as a reference threshold.

This comparative analysis provides insights into understanding long-term depreciation patterns between traditional internal combustion engine vehicles and newer electric vehicle technology in the sedan market segment.

3.5.2 Roberson et al. (2024) Model

Eq. 2, adapted from the model developed by Roberson et al. (2024), captures the interaction effects of vehicle age with fuel type, Tesla designation, mileage per year, and the logarithm of the manufacturer's suggested retail price (MSRP). This model allows for a more nuanced analysis of how depreciation varies across different powertrains over time. Figure 3.8 illustrates the depreciation patterns generated using the Roberson (2024) model specification and our dataset.

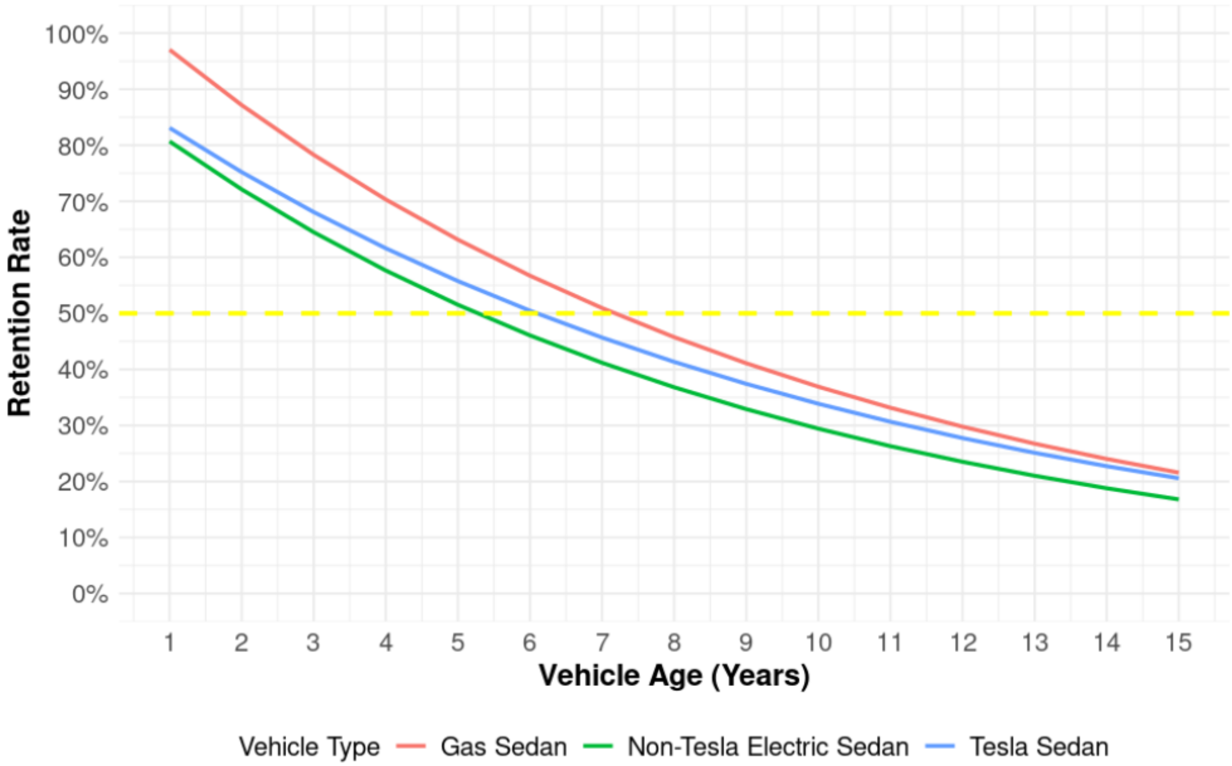

Fig. 3.8: The graph depicts the retention rate (y-axis) as a function of vehicle age (x-axis) for three vehicle categories: gas sedans, Tesla electric sedans, and non-Tesla electric sedans, set by Roberson et al. (2024) model. A horizontal yellow dashed line at the 50% retention rate serves as a reference threshold.

Key findings from Figure 3.8 reveal ICEV sedans exhibit the highest retention rates in the early years, starting at approximately 98%. Electric sedans that are not manufactured by Tesla (non-Tesla electric sedans) start with the lowest retention rates, around 80%. On the other hand, Tesla sedans maintain higher retention rates throughout the 15-year period, indicating slower depreciation compared to the other categories. Gas sedans show moderate depreciation, with retention rates consistently higher than both Tesla and non-Tesla electric sedans. Notably, Tesla sedans cross the 50% retention rate around year 6, non-Tesla electric sedans cross the threshold slightly earlier by year 5.5, and ICEV type sedans reach the 50% threshold around year 7.5, highlighting faster depreciation of BEVs compared to ICEVs.

3.5.3 All 3 Models

3.5.3.1 Depreciation Prediction Across ICEV Sedans

Figure 3.9 demonstrates the three models, showing consistency in depreciation projections where all three models exhibit a classic negative exponential depreciation pattern for ICEV types of Sedans. Roberson model projects marginally higher initial value retention compared to the other two models. As vehicles age, all models demonstrate a consistent decline in retention rates, crossing the 50% threshold (indicated by the horizontal dashed line) at approximately 7-year.

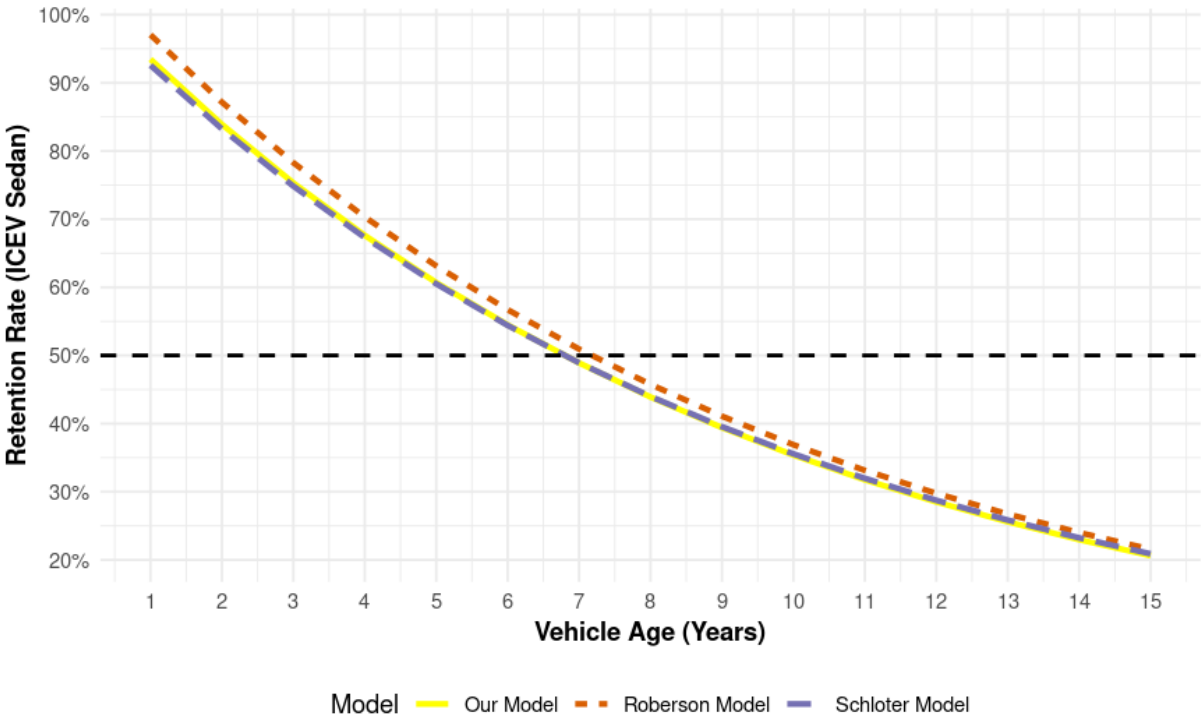

Fig. 3.9: The graph presents a comparative analysis of three distinct depreciation models for gas sedans: Our Model, the Roberson (2024) Model, and the Schloter (2022) Model. This visualization illustrates the retention rate trajectory as function of vehicle age over a 15-year period. A horizontal black dashed line at the 50% retention rate serves as a reference threshold.

The most accelerated depreciation occurs within the first five years, during which approximately 40–45% of the vehicle's value is lost across all models. Following this period, the rate of depreciation begins to moderate, with a more gradual decline observed between years eight and fifteen. By the end of the 15-year period, all models converge to retention rates of approximately 20–22%. While the models demonstrate strong overall agreement, subtle differences are evident in their early-stage projections. The Roberson (2024) model predicts slightly higher retention rates during the first seven years compared to both our model and the Schloter (2022) model. In contrast, our model and the Schloter (2022) model track almost identically throughout the entire 15-year period, with deviations of less than two percentage points at any given age. Notably, after year eight, all three models produce nearly identical depreciation projections, suggesting that differences in modeling assumptions primarily influence short-term depreciation estimates rather than long-term value retention outcomes.

The high degree of concordance between these independently developed models reinforces the reliability of the depreciation patterns identified for gas sedans. This consensus provides stakeholders—including manufacturers, financial institutions, insurers, and consumers—with greater confidence in making economic decisions related to vehicle valuation over time. The similar predicted depreciation curves also suggest that the fundamental economic factors driving gas sedan depreciation are well-captured by all three modeling approaches, despite potential differences in their underlying statistical formulations.

3.5.3.2 Depreciation Prediction Across Electric Sedans

The comparative analysis of depreciation models for electric sedans reveals distinct patterns in value retention over time, as can be seen in Figure 3.10.

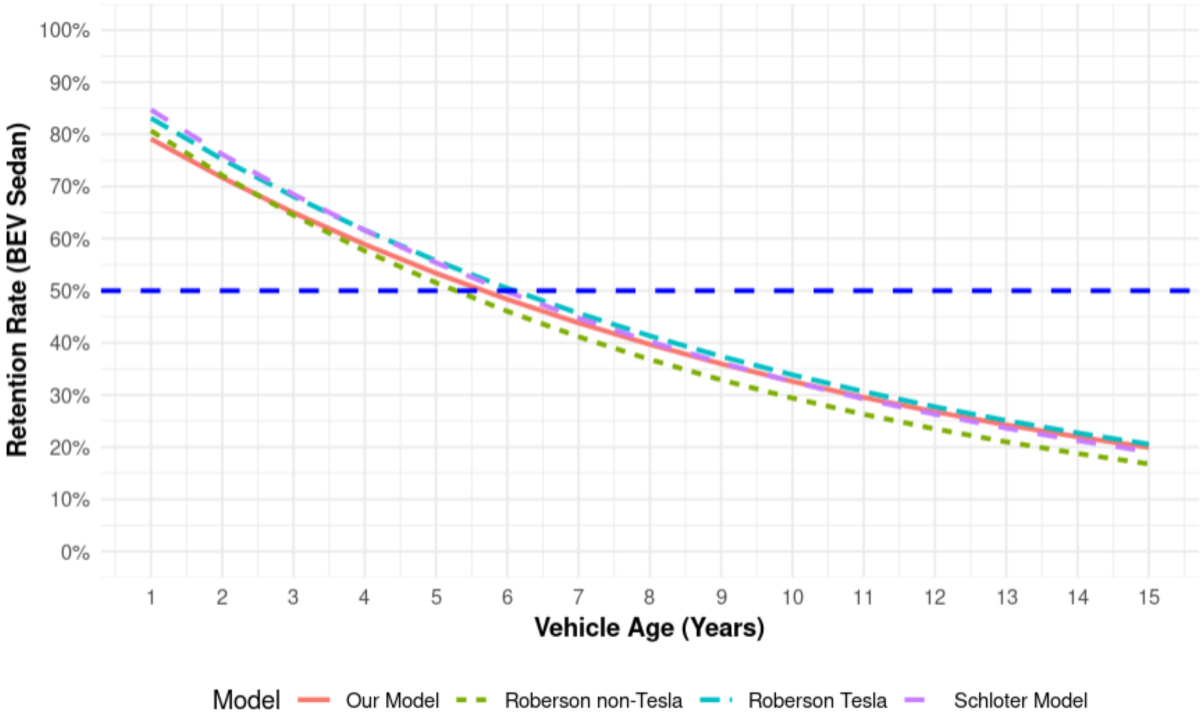

Fig. 3.10: Depreciation curves for electric sedans derived from three modeling approaches— our model, Schloter's (2022) model, and Roberson's (2024) model— illustrate the decline in value retention over time. The x-axis represents vehicle age in years (1-15), while the y-axis depicts the retention rate as a percentage of original value (0-100%). A horizontal blue dashed line at the 50% retention rate serves as a reference threshold.

Key observations from the depreciation analysis in Figure 3.10 reveal several important trends. First, new electric sedans exhibit lower initial retention rates relative to their gasoline counterparts. Depreciation is most pronounced within the first five to seven years across all models, reflecting accelerated early value loss due to technological obsolescence and the rapid evolution of electric vehicle (EV) technology. While all models predict a general decline in retention rates as vehicle age increases, notable differences emerge in their trajectories. Some models forecast slightly slower depreciation in the early years, while others show a more gradual decline during later stages. These variations highlight the sensitivity of depreciation estimates to modeling approaches, especially when incorporating interactions involving vehicle age, type, and brand differentiation (e.g., Tesla vs. non-Tesla). By year 15, the curves generally converge near a 20–22% retention rate, suggesting that despite initial discrepancies, long-term value erosion is a consistent outcome across all electric sedan models. eq 3.3 summarizes the key differences among the 3 models analyzed in our study.

Table 3.3: Key differences among the three models analyzed.

Feature	Our Model	Schloter (2022)	Roberson et. al (2024)
Data Source	Web-scraped dataset from Craigslist	Auction house data	Multiple listing platforms and dealerships
Geographic Scope	17 U.S. cities with varying climates	Multiple countries	Nationwide U.S.
Vehicle Powertrains	EVs vs. gasoline/diesel across multiple brands	Focused on ICE vehicles	Covers EV vs. gasoline
Response Variable	Price retention rate	Auction sale prices	Depreciation percent
Regression Type	Linear regression with interaction effects	Linear regression	Hedonic pricing model (with nonlinear effects)
Control Variables	MSRP, Mileage per Year, Powertrain, Class, Age, Seller Type	Auction-based controls	Brand-specific effects

This analysis provides evidence that although the early-stage depreciation trajectories for electric sedans differ based on the modeling approach, the long-term value trends converge, reflecting similar overall market depreciation. The differences observed in the early years may have important implications for investors and manufacturers, especially when considering the rapid pace of technological advancement in electric vehicles. Each model provides valuable insights into the underlying economic dynamics, with the variations highlighting the sensitivity of value retention to factors such as technological progress, battery degradation, and shifting consumer preferences. These findings can inform strategic decision-making regarding pricing, marketing, and investment in electric vehicle technology.

4. Study Limitations

4.1 Not Actual Transactions but Posted Price

One of the limitations of this study is the reliance on vehicle prices obtained from online listings on Craigslist rather than actual transaction prices. The posted prices on Craigslist may not accurately reflect the final agreed-upon sale price between buyers and sellers. These listed prices could potentially be inflated or negotiated downwards during the transaction process. Additionally, there may be variations in pricing strategies employed by individual sellers, such as intentionally listing a higher price with the expectation of negotiating or setting a lower price to attract more interest. This discrepancy between listed and actual transaction prices could introduce bias or noise into the data analysis, potentially skewing the results or reducing the accuracy of predictions derived from this data.

4.2 Vehicle Condition Classification

Vehicle condition in our dataset consists of three categories: Good, Like New, and Excellent. These designations primarily denote vehicles with minimal damage or stains in the interior, an absence of damage and alterations on the exterior, fully functional mechanical components, a clean title, and impeccable condition of wheels and other integral parts. The condition labels are self-reported by the owner or seller, and we are unable to verify the actual condition of the vehicles. Therefore, we do not include vehicle condition as a variable within our models.

4.3 "Clean" Title Criteria

The investigation exclusively considers vehicles with a "clean" title. As per the definition derived from Craigslist, a clean title pertains to a car that has never been involved in a serious accident, has not undergone odometer rollback, and has not been repurchased by the manufacturer due to a defect.

4.4 EV Feature Limitations

A key limitation of this study is the exclusion of specific electric vehicle attributes such as battery range, charging speed, drivetrain configuration, and software features, all of which can significantly influence resale value and consumer preferences. Due to data availability constraints, our analysis did not account for these detailed specifications, which may vary widely across EV models and production years. As a result, the depreciation patterns observed in this study may not fully capture the heterogeneity within the EV segment, potentially limiting the granularity of our findings. Future research incorporating these vehicle-level characteristics could provide deeper insights into the factors driving EV value retention.

4.5 Data Acquisition Source

While comparative analyses have been conducted from platforms such as Kelly Blue Book and Edmunds, we exclusively used data from Craigslist in this study. The study acknowledges the potential for enhanced real-time insights into used vehicle price depreciation through further investigation incorporating data from a spectrum of online platforms.

4.6 Market Disruptions and Policy Influence

Market disruptions such as the COVID-19 pandemic, semiconductor shortages, and broader supply chain shocks were not explicitly accounted for in this analysis. Additionally, government incentives, including federal and state-level tax credits or rebates, which significantly influence EV adoption[25] and thus the resale dynamics of electric vehicles, were also not incorporated. These exclusions may limit the generalizability of our results, especially for time periods or regions where such disruptions or policies had a pronounced effect on vehicle pricing and consumer behavior[26].

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[25] (Coffman et al., 2015) https://www-tandfonline-com.proxy.lib.umich.edu/doi/full/10.1080/01441647.2016.1217282

[26] (CBT News, 2024) https://www.cbtnews.com/decoding-the-decline-in-used-car-prices-and-whats-next-for-the-market/

5. Future Research Directions

5.1 Expand Data Sources

The current study relies solely on data collected from the Craigslist platform. Future research could expand the data collection to include multiple online platforms, auction houses, dealership inventories, and other sources. This would provide a more comprehensive and representative sample of the used vehicle market, enhancing the robustness and generalizability of the findings.

5.2 Impact of Government Policies and Incentives

Government incentives, tax credits, and other policy measures can significantly influence the adoption and affordability of used vehicles, especially EVs. Future studies could investigate how these factors affect the depreciation rates for used EVs across different regions or states.

5.3 Machine Learning Techniques for Predictive Modeling

The current study employs regression analyses and a specialized depreciation model. Future research could explore the potential integration of machine learning techniques, such as neural networks or ensemble methods, to develop more advanced predictive models for used vehicle price depreciation. These techniques could account for nonlinear relationships and incorporate a wider range of variables, potentially improving the accuracy and robustness of the models.

5.4 Energy Infrastructure and Cost

The availability of charging infrastructure and energy costs can influence the adoption and depreciation rates of used EVs in different geographic areas. Future studies could investigate the interplay between these regional factors, providing valuable insights into infrastructure planning and targeted incentives to promote EV adoption in specific regions.

5.5 Incorporating Dealer Engagement into Future Analysis

Future research should explore how wholesale competition and dealer perception affect used EV value retention. Given that 61% of dealers currently do not sell used EVs (Plug, 2025), incorporating dealer network dynamics into depreciation modeling may provide a more holistic understanding of secondary market outcomes.

6. Conclusion

This study provides a comprehensive analysis of the depreciation dynamics of electric vehicles relative to internal combustion engine vehicles in the U.S. used car market, leveraging a robust dataset of nearly 150,000 Craigslist listings and advanced regression modeling. The findings reveal nuanced patterns in value retention across powertrains, vehicle classes, and geographic regions, offering critical insights for stakeholders navigating the evolving automotive landscape. The results demonstrate that BEVs exhibit steeper initial depreciation, retaining approximately 40% of their value by the fifth year, compared to ICEVs' 60%. However, after about ten years, BEV depreciation begins to slow down. Notably, Tesla models outperformed non-Tesla BEVs in value retention over the first ten years and then this gap closed. Vehicle class emerged as a significant factor, with pickups and SUVs retaining more value than sedans, aligning with sustained demand for utility vehicles in the U.S. (ANL, 2022). Geographic analysis further highlighted regional differences: Boston and Dallas exhibited slower depreciation, whereas Miami and Detroit faced accelerated losses, potentially attributable to climatic and market dynamics. To build on this work, future studies should integrate multi-source data (e.g., auctions, dealerships) to enhance representativeness. Machine learning techniques could unravel nonlinear depreciation patterns, while investigations into charging infrastructure's impact on resale value would deepen understanding of EV adoption barriers. Overall, this study bridges critical gaps in understanding depreciation dynamics, offering a framework for consumers, industry stakeholders, and policymakers to optimize strategies for sustainable mobility.

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Appendix

Appendix A: Regional Variation in Depreciation

Table A shows a statistical summary of the location-based regression analysis.

Table A.1: Coefficients of location-based regression analysis.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.081e+00	5.707e-02	36.469	<2e-16 ***
Age	1.353e-01	6.493e-03	20.831	<2e-16 ***
fuelhybrid	7.498e-02	9.735e-03	7.703	1.34e-14 ***
fuelPHEV	4.753e-02	4.207e-02	1.130	0.258569
fuelelectric	-1.838e-01	1.129e-02	-16.282	<2e-16 ***
typepickup	1.101e-01	7.236e-03	15.219	<2e-16 ***
typeSUV	2.153e-02	4.344e-03	4.955	7.24e-07 ***
seller_typeowner	-1.237e-02	5.912e-03	-2.093	0.036358 *
odometer_by_age	-2.724e-05	1.576e-07	-172.799	<2e-16 ***
log(MSRP_avg)	-1.663e-01	5.404e-03	-30.766	<2e-16 ***
cityAtlanta	6.926e-02	1.660e-02	4.173	3.00e-05 ***
cityBoston	8.255e-02	1.514e-02	5.451	5.00e-08 ***
cityCleveland	1.727e-02	1.996e-02	0.865	0.386881
cityDallas	6.887e-02	1.309e-02	5.262	1.43e-07 ***
cityDenver	2.506e-02	1.209e-02	2.073	0.038209 *
cityDetroit	-6.427e-02	1.441e-02	-4.461	8.17e-06 ***
cityHouston	-1.669e-02	1.381e-02	-1.209	0.226821
cityLos Angeles	-7.727e-03	1.226e-02	-0.630	0.528552
cityMiami	-1.687e-01	1.343e-02	-12.559	<2e-16 ***
cityMinneapolis	4.530e-02	1.258e-02	3.602	0.000316 ***
cityNew York	-7.116e-02	1.224e-02	-5.812	6.19e-09 ***
cityPhiladelphia	2.008e-03	1.919e-02	0.105	0.916638
cityPhoenix	-4.268e-03	1.230e-02	-0.347	0.728609
citySan Francisco	3.686e-03	1.176e-02	0.313	0.753983
citySeattle	6.896e-03	1.209e-02	0.571	0.568248
cityWashington DC	3.656e-02	1.372e-02	2.664	0.007714 **
Age:fuelhybrid	-1.449e-03	1.122e-03	-1.292	0.196478
Age:fuelPHEV	-2.986e-03	5.588e-03	-0.534	0.593077
Age:fuelelectric	5.834e-03	1.871e-03	3.118	0.001818 **
Age:typepickup	3.018e-02	8.458e-04	35.687	<2e-16 ***
Age:typeSUV	2.384e-03	4.939e-04	4.827	1.39e-06 ***

```
Age:seller_typeowner  -1.142e-02  6.288e-04  -18.156    <2e-16 ***
Age:log(MSRP_avg)     -2.455e-02  6.205e-04  -39.575    <2e-16 ***
Age:cityAtlanta       -1.795e-03  1.788e-03   -1.004    0.315198
Age:cityBoston         7.285e-03  1.638e-03    4.448    8.68e-06 ***
Age:cityCleveland      5.950e-04  2.159e-03    0.276    0.782840
Age:cityDallas         1.159e-03  1.459e-03    0.794    0.427091
Age:cityDenver         1.802e-02  1.323e-03   13.623    <2e-16 ***
Age:cityDetroit        1.114e-02  1.626e-03    6.852   7.32e-12 ***
Age:cityHouston        6.161e-03  1.570e-03    3.923   8.74e-05 ***
Age:cityLos Angeles    1.469e-02  1.338e-03   10.985   <2e-16 ***
Age:cityMiami          1.257e-02  1.559e-03    8.064   7.44e-16 ***
Age:cityMinneapolis    3.403e-03  1.366e-03    2.492   0.012710 *
Age:cityNew York       1.355e-02  1.335e-03   10.155   <2e-16 ***
Age:cityPhiladelphia  -4.191e-04  1.963e-03   -0.214   0.830906
Age:cityPhoenix        1.516e-02  1.351e-03   11.219   <2e-16 ***
Age:citySan Francisco  2.126e-02  1.289e-03   16.492   <2e-16 ***
Age:citySeattle        2.245e-02  1.303e-03   17.228   <2e-16 ***
Age:cityWashington DC  3.244e-03  1.487e-03    2.181   0.029191 *
```

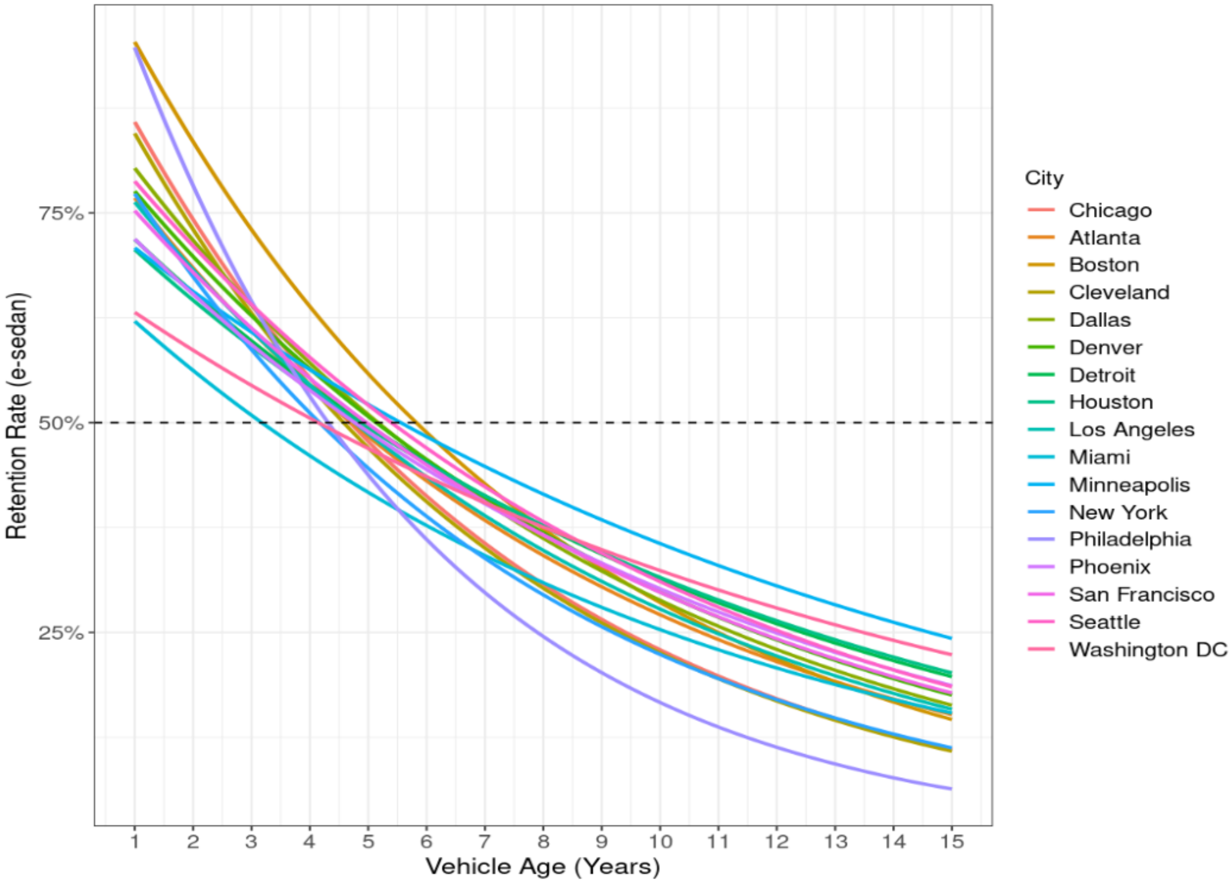

Fig. A.1: Retention rate of electric sedans over a 15-year period in the 17 cities analyzed in our study. X-axis represents the vehicle age in years (from 1 to 15 years old), y-axis represents value retention rate of the vehicle on a scale of 0 to 100%. A horizontal black dashed line at the 50% retention rate serves as a reference threshold.

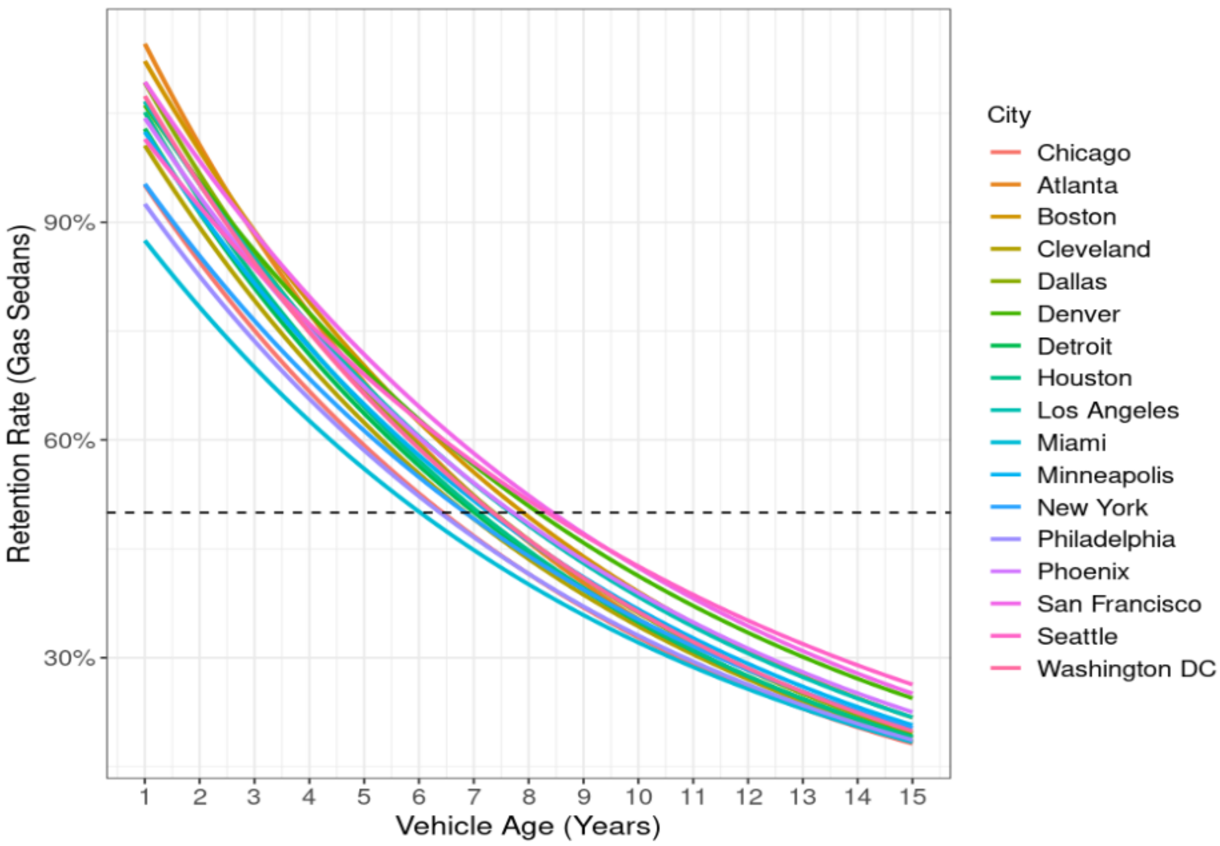

Fig. A.2: Retention rate of gasoline-powered sedans over a 15-year period in the 17 cities analyzed in our study. x-axis represents vehicle age in years (from 1 to 15 years old), y-axis represents value retention rate of the vehicle on a scale of 0 to 100%. A horizontal black dashed line at the 50% retention rate serves as a reference threshold.

Appendix B: Effect of Winter Road Salting in Vehicle Value Retention

Table B.1: Coefficient table of the road salting-based regression model (Eq. 4).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2.230e+00	5.783e-02	38.560	< 2e-16 ***
Age	1.317e-01	6.594e-03	19.975	< 2e-16 ***
fuelhybrid	1.044e-01	1.123e-02	9.295	< 2e-16 ***
fuelPHEV	6.452e-02	4.673e-02	1.381	0.167395
fuelelectric	-1.588e-01	1.231e-02	-12.900	< 2e-16 ***
Salting	5.921e-02	8.510e-03	6.958	3.48e-12 ***
typepickup	1.186e-01	8.743e-03	13.562	< 2e-16 ***
typeSUV	1.824e-02	5.079e-03	3.591	0.000329 ***
odometer_by_age	-2.824e-05	1.616e-07	-174.714	< 2e-16 ***
log(MSRP_avg)	-1.797e-01	5.563e-03	-32.306	< 2e-16 ***
seller_typeowner	-1.180e-01	2.067e-03	-57.081	< 2e-16 ***
Age:fuelhybrid	-1.539e-03	1.302e-03	-1.182	0.237170
Age:fuelPHEV	4.531e-05	6.278e-03	0.007	0.994241
Age:fuelelectric	7.268e-03	2.074e-03	3.504	0.000459 ***
Age:Salting	-9.247e-03	9.316e-04	-9.927	< 2e-16 ***
fuelhybrid:Salting	-6.637e-02	2.475e-02	-2.682	0.007313 **
fuelPHEV:Salting	-2.479e-02	1.294e-01	-0.192	0.848065
fuelelectric:Salting	3.402e-02	3.347e-02	1.017	0.309355
Age:typepickup	2.840e-02	1.028e-03	27.629	< 2e-16 ***
Age:typeSUV	2.237e-03	5.840e-04	3.832	0.000127 ***
Salting:typepickup	9.535e-03	1.625e-02	0.587	0.557335
Salting:typeSUV	1.983e-02	1.029e-02	1.928	0.053897 .
Age:log(MSRP_avg)	-2.305e-02	6.383e-04	-36.106	< 2e-16 ***
Age:fuelhybrid:Salting	5.105e-03	2.803e-03	1.821	0.068555 .
Age:fuelPHEV:Salting	1.489e-03	1.621e-02	0.092	0.926822
Age:fuelelectric:Salting	-3.550e-03	5.428e-03	-0.654	0.513143
Age:Salting:typepickup	5.993e-03	1.901e-03	3.153	0.001615 **
Age:Salting:typeSUV	9.924e-04	1.153e-03	0.861	0.389437

Appendix C: Winter Road Salting in Selected Cities

Table C.1: Cities in our dataset were assigned a binary number based on whether they use road salt during winter or not.

City	Salting Status	Binary Number Assigned
Minneapolis	Regularly Use Salt	1
Chicago	Regularly Use Salt	1
Detroit	Regularly Use Salt	1
Cleveland	Regularly Use Salt	1
Boston	Regularly Use Salt	1
Denver	Regularly Use Salt	1
Seattle	Usually do not use Salt	0
New York City	Usually do not use Salt	0
Philadelphia	Usually do not use Salt	0
Washington, DC	Usually do not use Salt	0
San Francisco	Usually do not use Salt	0
Los Angeles	Usually do not use Salt	0
Atlanta	Usually do not use Salt	0
Houston	Usually do not use Salt	0
Dallas	Usually do not use Salt	0
Miami	Usually do not use Salt	0
Phoenix	Usually do not use Salt	0