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Subsidies for New Electric Vehicle Purchases and Their Impact on Used Vehicle Prices: Evidence from Japan[1]

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Abstract

This study examines Japan's used-vehicle market from 2014 to 2023 to assess the depreciation of used electric vehicle (EV) prices and the effects of new-EV subsidies on those prices. We first analyze EV residual values, defined as used-vehicle prices relative to new-vehicle purchase prices net of subsidies, by comparing them with those of matched hybrid vehicles (HVs). We next estimate the probability that a used EV is sold, modeling this probability as dependent on subsidies for new EVs. A simple pricing model is then used to examine how the estimated subsidy effects translate into changes in used EV prices. Our analysis shows that among vehicles with low mileage or young vehicle ages, EV residual values are 10-12 percentage points lower than those of HVs. The sale-probability estimates show that subsidies for new EV purchases reduce used-vehicle sale probabilities for one particular type of EV: battery electric vehicles (BEVs). However, the simulation suggests that subsidies have only a limited effect on used BEV prices. Although low residual values may discourage EV adoption, the estimated subsidy-induced price reduction appears to explain only a small part of the residual value gap between EVs and HVs.

Keywords: electric vehicles; subsidies; used vehicle prices; residual value; propensity score matching; Japanese automobile market
JEL classification: H23; L13; L62

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1 Introduction

Electrification is widely regarded as a key pathway for decarbonizing the transport sector (IEA (2025)), prompting many countries to adopt subsidies to promote electric vehicles (EVs). Although these subsidies typically target purchases of new EVs, new-vehicle buyers do not necessarily keep their vehicles until they are fully depreciated. Given the durable nature of automobiles, trade-in values of used EVs may be a key element in adopting new EVs. In particular, the usability of EVs, including the costs associated with charging, may be difficult to assess before purchase, giving EVs characteristics of experience goods. Consumers who find EVs less usable than expected may choose to replace them, potentially making expected trade-in values more important when purchasing a new EV than when purchasing a conventional gasoline vehicle. In this study, we examine how used EV prices depreciate over the course of vehicle use and how they are affected by subsidies for new EV purchases.

In analyzing the effects of subsidies for new EVs, we focus on consumers' choices between new and used vehicles at the time of purchase. In particular, subsidies may induce consumers to substitute new vehicles for used vehicles, thereby reducing demand for used vehicles and lowering their prices. The decline in used-vehicle prices may be associated with lower trade-in values, which may partially offset the positive effects of subsidies on new-vehicle sales. However, when new-vehicle production is constrained by capacity, subsidy-induced increases in demand may lengthen delivery times, shifting demand toward immediately available used vehicles and thereby raising their prices. These opposing effects on demand for used vehicles and their prices make the overall effect of subsidies ambiguous, motivating an empirical investigation. We examine how these effects differ across EV types: battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHVs), and fuel-cell electric vehicles (FCVs).

To conduct the analyses discussed above, we examine Japan's used-vehicle market from 2014 to 2023 using data provided by a major online platform for used vehicles. The data cover more than 10,000 distinct used EVs, despite the limited penetration of EVs in Japan. We begin by analyzing depreciation using residual values, defined as the ratios of used-vehicle prices to the net purchase prices of the corresponding new vehicles. Specifically, we compare the residual values of EVs with those of hybrid vehicles (HVs), which were regarded as environmentally friendly alternatives before the emergence of EVs. Because HVs are far more numerous in the second-hand market and span a broader range of market segments (e.g., body types) than EVs, a matching analysis is employed to improve comparability between the two groups. Next, we analyze the sale probabilities of used EVs using matched used HVs for comparison. In particular, we assess the effects of subsidies on sale probabilities, allowing these effects to vary across EV types. We further examine how these effects translate into changes in used-vehicle prices, based on a simple model of used-vehicle pricing.

The findings are summarized as follows. First, the residual-value analysis shows that EVs have lower residual values than HVs with similar attributes, particularly among vehicles with lower mileage or younger age. Specifically, the residual values of EVs are 10–12 percentage points lower than those of HVs in the first four quintiles of both mileage and vehicle age in our sample. Because

residual values are calculated using net purchase prices (i.e., new-vehicle prices net of subsidies), these results suggest that consumers who trade in their EVs relatively early incur greater depreciation as a proportion of their net purchase prices, even after accounting for EV purchase subsidies. Depreciation patterns also differ across EV types.

Second, the sale-probability estimates indicate little overall effect of subsidies on EV sale probabilities, although the effects differ across EV types. In particular, subsidies reduce the sale probability of BEVs, suggesting that new and used BEVs are substitutes. By contrast, subsidies increase the sale probability of PHVs, although this effect is weakly significant.

Third, the counterfactual simulation indicates that subsidies reduce markups on BEVs, implying lower used-vehicle prices and a 1.1-percentage-point reduction in residual values if the other components of the pricing equation remain unchanged. This effect is small relative to the residual-value gap between BEVs and HVs. Although low residual values may contribute to limited EV adoption in Japan, the estimated subsidy-induced price reduction appears to account for only a small part of the observed gap.

Related literature

This study relates to several recent strands of the literature on EVs. One strand examines various factors affecting the EV adoptions. This includes the analysis of EV subsidies, accounting for indirect network effects between EV adoption and public charging infrastructure (Li et al. (2017); Zhou and Li (2018); Springel (2021); Li (2023); Fournel (2025)), vehicle attribute choices, particularly battery capacity (Barwick, Kwon, and Li (2024); Remmy (2026)), and industrial policy considerations (Allcott et al. (2026)). This also includes the examination on the effects of gasoline prices (Bushnell, Muehlegger, and Rapson (2022)), peer effects (Tebbe (2025)), income and educational attainment (Muehlegger and Rapson (2022); Gillingham et al. (2023)), and political ideology (Gillingham et al. (2025); Davis, Li, and Springel (2026)). While these studies focus on the new-vehicle market, few studies examine used EVs and their implications for the new-vehicle market. One exception is Allcott, Kwon and Snyder (2024), which examines the efficiency and distributional effects of subsidies for used EVs under the US Inflation Reduction Act using a dynamic model of new- and used-vehicle markets.

Another strand examines the costs incurred during EV ownership, particularly charging costs. Dorsey, Langer, and McRae (2025) estimate charging time costs indirectly from the refueling behavior of gasoline-vehicle drivers, whereas Sunada and Xia (2026) estimate them directly from the charging behavior of EV drivers. Our study contributes to this literature by providing evidence on the depreciation of used EV prices, which represents another component of the costs consumers bear over the course of EV ownership.

This study also relates to research on the Japanese automobile market, including the analyses of the subsidy measure with cash-for-clunkers program during the financial crisis (Kitano (2022, 2025)), subsidy and tax incentives after the Great East Japan Earthquake (Konishi and Zhao (2017)), and attribute-based fuel economy regulation (Ito and Sallee (2018); Konishi and Managi (2020)). While

these studies examine conventional vehicles, we focus on Japan's EV market, where EV penetration remains limited.

The rest of the paper is organized as follows. Section 2 provides an overview of the Japanese EV market, including the subsidy measures in effect during the study period. Section 3 describes the used-vehicle data and presents a preliminary analysis of residual values. Section 4 introduces a simple model of used-vehicle pricing based on sale probabilities, estimates these probabilities, and conducts counterfactual simulations to assess the implications of subsidies for residual values. Section 5 concludes.

2 Institutional background

This study examines Japan's used-vehicle market from 2014 to 2023. This section provides an overview of the Japanese EV market and the subsidy measures in effect during the study period.

The EVs considered in this study comprise three types: BEVs, vehicles powered solely by electricity stored in a battery; PHVs, vehicles combining an externally rechargeable battery with an internal combustion engine; and FCVs, vehicles powered by electricity generated from hydrogen using a fuel cell. Although FCVs have received relatively little attention in the EV literature,[1] we include them in our analysis because they have been eligible for subsidies under Japan's policy programs promoting next-generation vehicles. Moreover, as discussed below, per-vehicle subsidies for FCVs have been substantially larger than those for BEVs and PHVs, providing useful variation for examining the effects of subsidies on the market.

2.1 Japanese EV market

Japan was among the leading countries in new EV sales in the early 2010s, when early EV models such as the Nissan LEAF were introduced to the market. Figure 1 shows Japan's ranking in annual EV sales among countries covered by the *MarkLines* database. MarkLines is a fee-based automotive information platform and provide the data related to the automobile market worldwide, including the new EV sales. The countries and regions covered by the data are provided in Appendix A.

The figure shows that Japan ranked among the top three through 2015, alongside China and the United States, both of which have much larger new-vehicle markets. However, Japan's relative position deteriorated from the late 2010s. Its ranking fell to 14th in 2020 and 2021, behind countries with smaller overall new-vehicle markets, such as Korea, Norway, and Sweden.[2]

While EV sales remained limited in Japan, sales of HVs, previously regarded as environmentally friendly vehicles, remained consistently high. As shown in Figure 2, annual HV sales remained above

[1] One exception is Davis, Li, and Springel (2026), which includes FCVs in its analysis of political ideology and EV adoption.

[2] Japan's ranking improved from 14th in 2021 to ninth in 2023, but this recovery did not persist: it fell back to 14th in 2024.

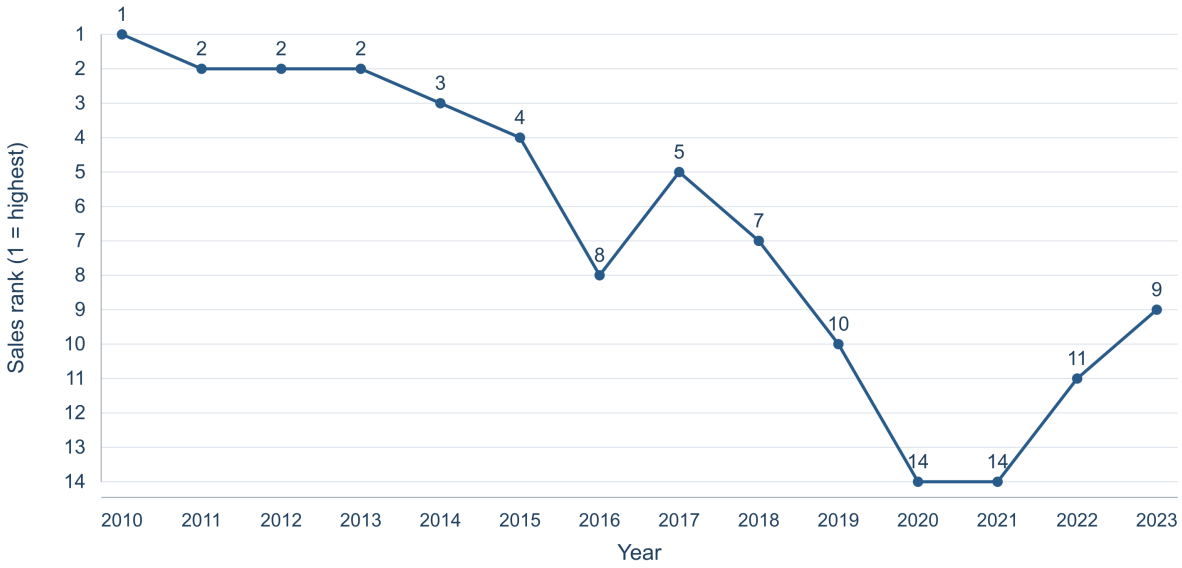


Figure 1: Japan's rank in EV sales

Notes: Rankings are based on annual EV sales among countries covered by the MarkLines database. EVs comprise BEVs, PHVs, and FCVs.

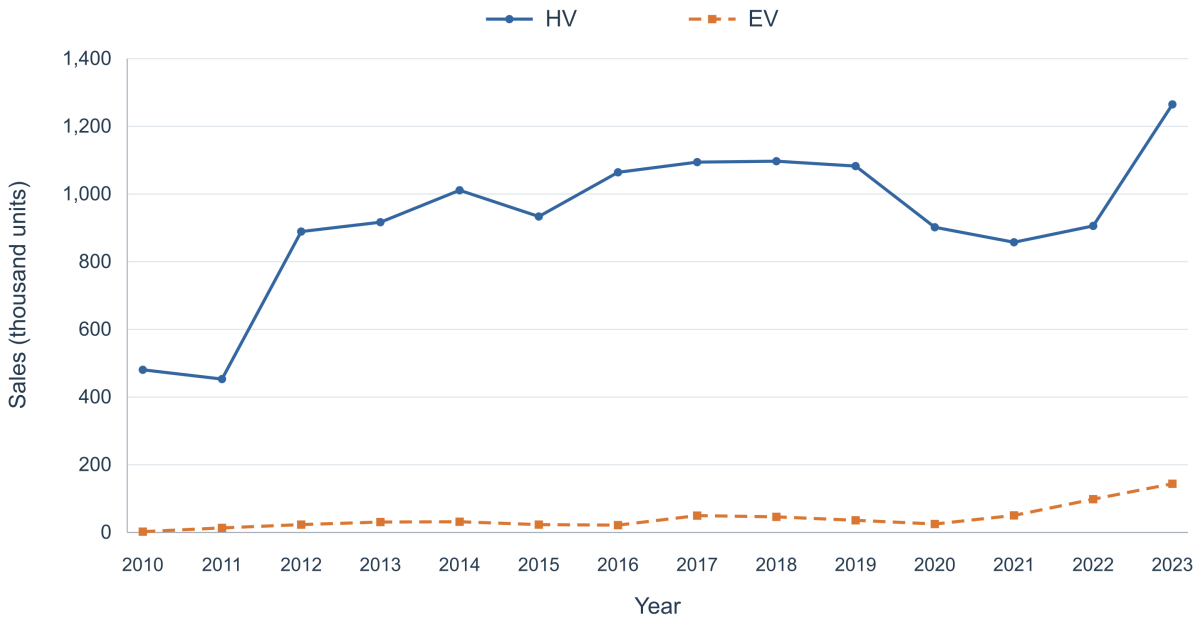


Figure 2: New EV and HV sales in Japan

Notes: The figure shows annual new-vehicle sales in Japan based on the MarkLines database. EVs comprise BEVs, PHVs, and FCVs. HVs exclude mild hybrids. Sales are measured in thousands of vehicles.

0.8 million from 2013 onward and exceeded 1.2 million in 2023. By contrast, EV sales remained much lower than HV sales, although they increased from 2020 to 2023.

2.2 EV subsidy

Purchases of new EVs in Japan have been subsidized by the government since their introduction. The subsidy schedule is typically revised at the beginning of each fiscal year (FY), which starts in April in Japan. Data on EV subsidy amounts are obtained from documents published by the *Next Generation Vehicle Promotion Center*, the organization responsible for administering subsidy applications.[3]

Figure 3 shows mean subsidy amounts by EV type. Because per-unit subsidy amounts differ across vehicle models and trims within each EV type, we calculate the mean subsidy amount for each type and fiscal year. As shown in the figure, the per-unit subsidy for FCVs was initially set at 2 million Japanese yen ($\approx$ 18,700 US dollars),[4] substantially more than those for BEVs and PHVs. Subsidy amounts also vary over time, especially for BEVs and PHVs.

Notably, EV subsidies have been substantially larger than those previously offered for fuel-efficient vehicles. Specifically, a large-scale subsidy program covering a wide range of gasoline and hybrid vehicles was available from December 2011 to September 2012, but its per-unit subsidy amounts were much smaller than those for EVs: 100,000 yen for standard-sized vehicles and 70,000 yen for mini-vehicles. Subsidies for gasoline and hybrid vehicles have not been available since October 2012.

3 Preliminary analysis

To examine EV adoption from a durable-goods perspective, we first analyze the residual values of EVs, defined as the ratios of used-vehicle prices to new-vehicle purchase prices net of subsidies,

Table 1: Number of Months Observed per Used Vehicle by Vehicle Type

Type	No. of vehicles	Mean	SD	Min	P25	Median	P75	Max
All	349803	2.702	2.519	1	1	2	3	35
HV	336061	2.701	2.520	1	1	2	3	35
EV	13742	2.713	2.494	1	1	2	3	33
BEV	5530	2.844	2.493	1	1	2	4	30
PHV	7336	2.575	2.399	1	1	2	3	33
FCV	876	3.035	3.121	1	1	2	4	33

Notes: No. of vehicles reports the number of distinct used vehicles by vehicle type. Mean, SD, Min, P25, Median, P75, and Max are calculated from the number of months in which each vehicle is observed in the monthly listing data.

[3]These documents are available on the website of the Next Generation Vehicle Promotion Center (`https://www.cev-pc.or.jp/`).

[4]The exchange rate averaged approximately 107 yen per US dollar over 2010–2023, although it fluctuated substantially over time, with annual averages ranging from approximately 80 to 140 yen. The exchange-rate data are obtained from the International Monetary Fund (`https://data.imf.org/`). We use this period average to convert yen amounts into US dollars.

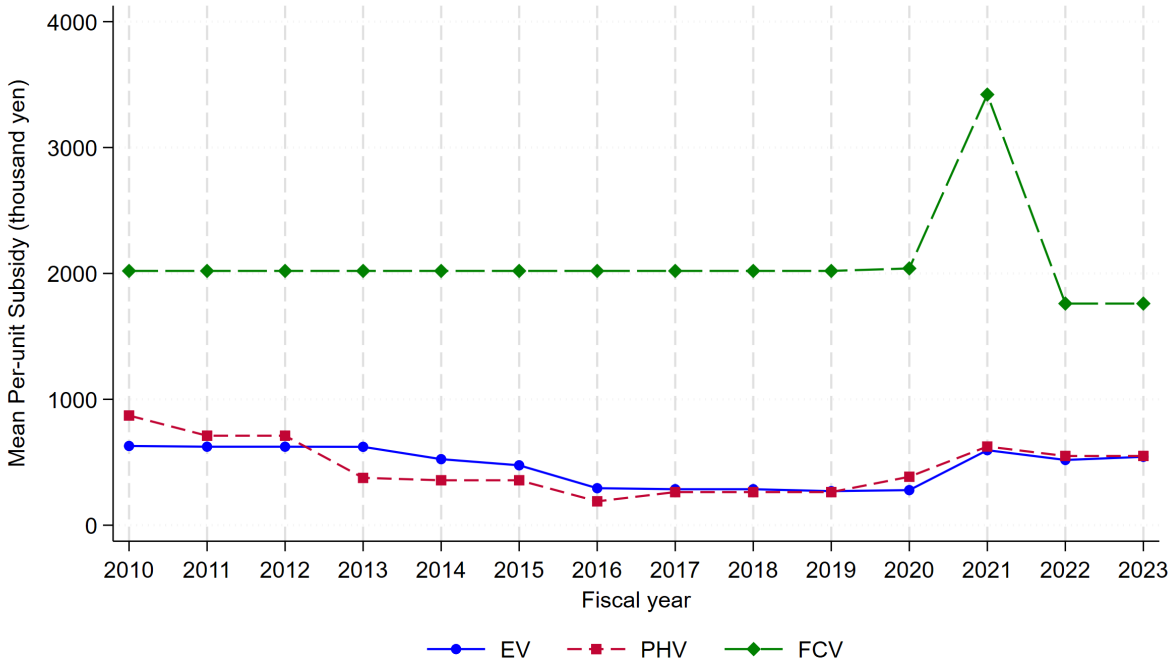


Figure 3: Mean Per-unit Subsidy by EV Type

Notes: This figure shows mean per-unit subsidy amounts by EV type and fiscal year. Subsidy amounts vary across vehicle models and trims within each EV type and are averaged for each type and fiscal year. For reference, the exchange rate averaged approximately 107 yen per US dollar over 2010–2023.

because residual values are a key determinant of vehicle choice. Before turning to examine the residual values, we introduce the used vehicle data and the sample restriction for the analysis.

3.1 Used vehicle data

Our primary dataset was provided by *PROTO Corporation*, which operates *Goo-net*, one of Japan's two largest online platforms for used-vehicle listings. For every vehicle listed for sale, the dataset identifies the model and the specific trim level within that model. It reports the vehicle's price, odometer reading (in kilometers), and year and month of registration. The dataset also contains catalog information for each model–trim combination, including the suggested list price, body type (e.g., hatchback, sedan, or SUV), and vehicle attributes such as length, width, and height.

We observe the stock of listings on the first day of each month from January 2014 through December 2023. Each listed vehicle has a unique identifier, allowing us to track it across months if it remains on the platform for multiple periods. The platform is used by numerous used-car dealers, who add and remove vehicle listings. Each dealer has a contract with PROTO that specifies the number of vehicles it may list on the platform. A listing may be removed when the vehicle is sold or for other reasons; for example, a dealer may transfer an unsold vehicle to another dealer through a used-vehicle auction or replace its listing with that of another vehicle because of the contractual

limit on the number of listings. The dataset allows us to distinguish between removals due to sales and those for other reasons. We define a monthly sale indicator, $Sold_{jt}$, which equals one if vehicle j, listed at the beginning of period t, is recorded as sold during that period, and zero otherwise.

As stated in the previous section, the subsidy program for gasoline and hybrid vehicles was commenced in December 2011 as part of a fiscal stimulus package to mitigate the adverse economic effects of the Great East Japan Earthquake in March 2011. In this study, we focus on the period during which only EVs were eligible for the subsidy and accordingly restrict the sample to used vehicles registered after FY2012.

We further restrict the sample as follows. First, we focus on vehicle models with more than 1,000 observations.[5] Second, we use hybrid vehicles (HVs), rather than conventional gasoline vehicles, as the comparison group for EVs because HVs are generally regarded as more environmentally friendly. Third, we exclude vehicles powered by diesel or premium (high-octane) gasoline. In our data, vehicles requiring premium gasoline are predominantly imported models. After applying these three restrictions, only domestic vehicle models remain in our sample; specifically, the EV model this study covers are the following: LEAF, I-MIEV for BEV; PRIUS PHV and OUTLANDER PHV for PHV; MIRAI for FCV. Fourth, we exclude used vehicles observed in the listing data for 36 months or more, as well as those whose odometer readings decrease or increase by 2,000 km or more between their first and last observations.

Given these sample restrictions, our sample consists of 349,803 distinct used vehicles: 13,742 EVs and 336,061 HVs, as shown in Table 1. The table also shows that the average number of months observed in the monthly listing data ranges from 2.6 to 3.0 across vehicle types. In addition, 75% of used vehicles are observed for three months or fewer.

3.2 Residual value

We first examine how vehicle values depreciate with use by analyzing the prices of used vehicles listed on the platform. One concern in calculating residual values is that listing prices are set by dealers and may differ from actual transaction prices. We therefore use the last observed listing prices before removal, restricting the sample to listings recorded as having ended in a sale, because these prices are likely to be better proxies for transaction prices.

Figure 4 shows binscatter plots of used-vehicle prices relative to new-vehicle list prices by vehicle type, before accounting for subsidies. As shown in the figure, the average price ratio for HVs is close to one for barely used vehicles, that is, vehicles with odometer readings close to zero. This implies that used HV prices are close to their new-vehicle list prices when the vehicles have been driven very little. By contrast, the price ratio for BEVs is about 0.8 for barely used vehicles, and that for FCVs is much lower, at about 0.5. These patterns suggest substantial depreciation even among vehicles that have been driven very little, especially BEVs and FCVs. However, the price ratio for PHVs is not much lower than that for HVs for barely used vehicles, suggesting that depreciation

[5]Each distinct used vehicle can be observed in multiple periods, so the number of observations may exceed the number of distinct vehicles.

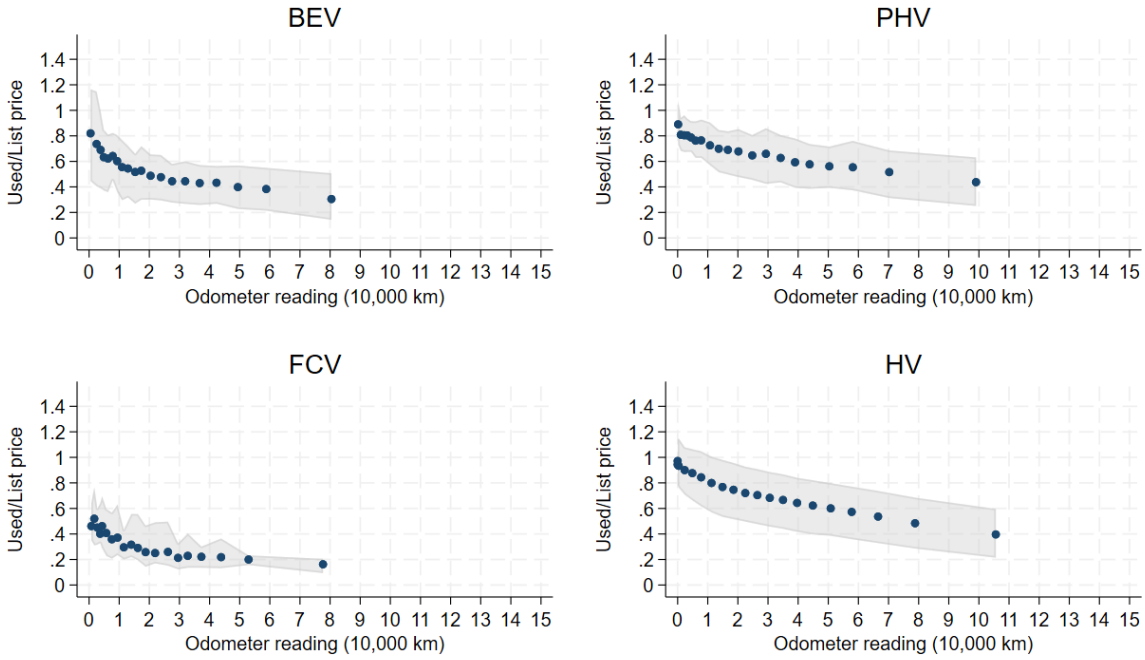


Figure 4: Used-Vehicle Prices Relative to New-Vehicle List Prices, by Vehicle Type

Notes: This figure presents binscatter plots of used-vehicle prices relative to new-vehicle list prices by vehicle type for vehicles recorded as sold. The ratio is calculated using the last observed used-vehicle price and the corresponding new-vehicle list price, without deducting subsidies. The points show the average price ratio for each odometer-reading bin, while the shaded areas show the range between the 5th and 95th percentiles within each bin. The numbers of observations are 2,778 for BEVs, 3,239 for PHVs, 421 for FCVs, and 215,439 for HVs.

patterns differ across EV types.

Figure 5 presents residual values, calculated using new-vehicle purchase prices net of the subsidies available at initial registration. Accounting for subsidies raises the price ratios for EVs relative to those shown in Figure 4, particularly for FCVs, which receive larger subsidies. These residual values measure value retention relative to the initial purchase cost borne by consumers. However, differences across vehicle types may also reflect differences in vehicle attributes, age, and usage. We therefore turn to a matching analysis to compare EVs with HVs that have similar characteristics.

3.3 Matching analysis

EV listings have been far less numerous than HV listings. Similar to the situation in the US EV market (Gillingham et al. (2023)), many market segments, such as certain body types and price ranges, have been underserved, with few EV models available in those segments. To examine differences in residual values between EVs and HVs more precisely, we compare EVs with HVs that have similar attributes.

For this analysis, we first select HV models in market segments where EV models are available

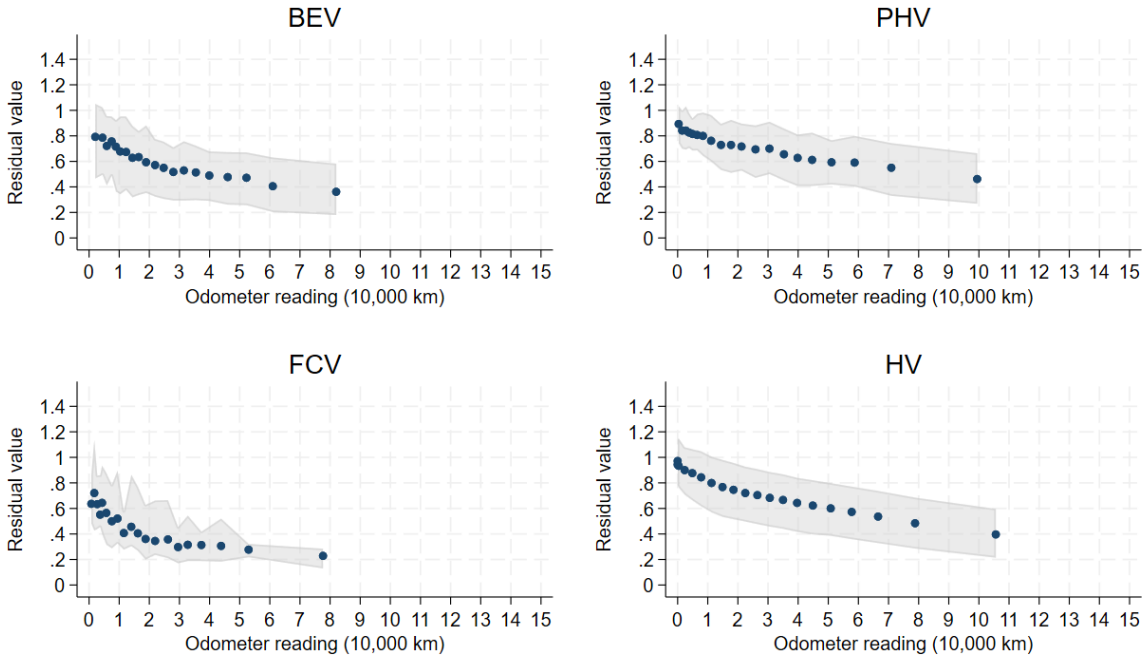


Figure 5: Residual Values by Vehicle Type

Notes: This figure presents binscatter plots of residual values by vehicle type for vehicles recorded as sold. The residual value is defined as the ratio of the last observed used-vehicle price to the net purchase price of the corresponding new vehicle, defined as its list price minus the subsidy amount at initial registration. The points show the average residual value for each odometer-reading bin, while the shaded areas show the range between the 5th and 95th percentiles within each bin. The numbers of observations are 2,309 for BEVs, 3,110 for PHVs, 421 for FCVs, and 215,436 for HVs.

and then apply nearest-neighbor matching. We use the last observed listing for each vehicle recorded as sold, so each vehicle contributes one observation to the matching sample. We estimate a linear probability model in which the dependent variable is an EV indicator and use the fitted values as matching scores. The explanatory variables are vehicle age, mileage (odometer reading), footprint (= length × width), height, and the new-vehicle price net of the subsidy at the time of purchase (i.e., $p_{jt'}^{new} - S_{jt'}$). Each EV is matched to the three nearest-neighbor HVs.[6] Details of the estimation results and the assessment of common support are provided in Appendix B.

Table 2 shows covariate balance before and after matching. After matching, the absolute standardized mean differences (SMDs) are below 0.1 for all variables except mileage.[7] Although the post-matching absolute SMD for mileage remains slightly above 0.1, we compare EVs and HVs within common mileage quintiles to limit comparisons between vehicles with substantially different mileage. This stratification does not necessarily eliminate all within-quintile differences. A notable

[6] As robustness checks, we also considered alternative matching specifications, including two nearest neighbors and logit-based propensity scores. The main results are qualitatively unchanged across these alternatives, while the baseline specification provides the most stable overall covariate balance.

[7] An absolute SMD below 0.1 is often used as a benchmark for negligible imbalance, although there is no universally accepted threshold (Austin (2009)).

Table 2: Covariate balance before and after matching

	Before matching				After matching			
Variable	EV	HV	Diff.	SMD	EV	HV	Diff.	SMD
Footprint (m^2)	8.14	7.09	1.04	1.05	8.14	8.15	-0.01	-0.02
Height (m)	1.54	1.55	-0.02	-0.18	1.54	1.54	0.00	-0.05
Vehicle age (months)	41.35	40.51	0.84	0.03	41.35	43.64	-2.29	-0.09
Mileage (10,000 km)	2.63	2.85	-0.22	-0.08	2.63	3.00	-0.38	-0.14
Net purchase price (million yen)	3.61	2.60	1.01	1.12	3.61	3.59	0.02	0.02
No. of vehicles	5,766	146,283			5,766	11,974		

Notes: The sample is restricted to vehicles whose listings are recorded as having ended in a sale. The EV and HV columns report the mean of each variable. The number of nearest neighbors is set to 3. SMD denotes the standardized mean difference, defined as the EV–HV mean difference divided by the square root of the average of the within-group variances.

Table 3: Mean residual values by mileage and vehicle age

Mileage					Vehicle age				
Quintile	EV	HV	Diff.	SE	Quintile	EV	HV	Diff.	SE
Q1 (≤5,200 km)	0.81	0.93	-0.12	0.03	Q1 (≤17 months)	0.84	0.94	-0.10	0.02
Q2 (5,200-13,596 km)	0.73	0.84	-0.11	0.04	Q2 (17-28 months)	0.75	0.87	-0.12	0.03
Q3 (13,596-26,689 km)	0.63	0.75	-0.12	0.04	Q3 (28-51 months)	0.64	0.74	-0.10	0.04
Q4 (26,689-44,471 km)	0.57	0.68	-0.11	0.05	Q4 (51-63 months)	0.53	0.62	-0.10	0.05
Q5 (>44,471 km)	0.49	0.48	0.02	0.05	Q5 (>63 months)	0.47	0.49	-0.02	0.06

Notes: The table is based on the matched sample. The quintile cutoff values are constructed using the distribution of EV listings. The EV and HV columns report mean residual values. Diff. denotes the EV mean minus the HV mean, and SE denotes the corresponding standard error.

improvement is the substantial reduction in the difference in net purchase prices after matching, allowing us to compare EVs and HVs in similar price ranges.

Table 3 reports the mean residual values of EVs and HVs by mileage and vehicle age quintile. The quintile cutoff values are constructed using the distribution of EV listings. Here, residual values are measured relative to subsidy-adjusted purchase prices. A key finding is that the mean residual values of EVs are 10–12 percentage points lower than those of HVs in the first four quintiles of both mileage and vehicle age, and these differences are statistically significant.

This finding suggests that EV ownership could still involve substantial depreciation for consumers who traded in their vehicles relatively early, even after accounting for purchase subsidies. Given that net purchase prices are similar between EVs and HVs after matching, the lower residual values of EVs suggest that consumers incur greater depreciation costs when purchasing EVs, even after accounting for purchase subsidies. In particular, because EVs were still a relatively new technology, consumers might have faced uncertainty about their convenience and usability before purchase. Consumers who found an EV inconvenient after purchase might therefore have wished to replace it at an early stage of ownership. Consequently, uncertainty about trade-in values could make purchasing an EV risky even with a subsidy.

Table 4: Differences in mean residual values relative to HVs, by EV type

	Mileage			Vehicle age		
Quintile	BEV−HV	PHV−HV	FCV−HV	BEV−HV	PHV−HV	FCV−HV
Q1	-0.15(0.03)	-0.09(0.02)	-0.31(0.01)	-0.12(0.02)	-0.09(0.02)	-0.22(0.01)
Q2	-0.13(0.03)	-0.05(0.03)	-0.34(0.02)	-0.14(0.03)	-0.09(0.03)	-0.20(0.02)
Q3	-0.16(0.02)	-0.03(0.02)	-0.37(0.02)	-0.16(0.02)	-0.04(0.02)	-0.20(0.02)
Q4	-0.17(0.02)	-0.02(0.04)	-0.36(0.02)	-0.14(0.03)	0.01(0.04)	-0.30(0.03)
Q5	-0.06(0.03)	0.08(0.05)	-0.22(0.03)	-0.07(0.04)	0.05(0.06)	-0.22(0.04)

Notes: The table is based on the matched sample. The quintiles are defined using the cutoff values reported in Table 3. The BEV−HV, PHV−HV, and FCV−HV columns report the corresponding differences in mean residual values. Standard errors are reported in parentheses.

Table 4 reports differences in mean residual values by EV type, revealing heterogeneity in depreciation patterns. In particular, the mean residual values of BEVs are 12–17 percentage points lower than those of HVs in the first four quintiles of both mileage and vehicle age. In the fifth quintile, the differences narrow to 6–7 percentage points. The differences are substantially larger for FCVs: their mean residual values are 22–37 percentage points lower than those of HVs across all mileage quintiles. Across all quintiles, PHVs have higher residual values relative to HVs than BEVs and FCVs do. In the higher quintiles, the mean residual values of PHVs even exceed those of HVs, although these positive differences are not statistically significant at the 5% level. Thus, the lower residual values of PHVs relative to HVs are most pronounced among relatively new and lightly used vehicles. This finding suggests that PHVs may involve less depreciation risk than other EV types for consumers considering an early replacement.

So far, we have found that EVs generally have lower residual values than HVs, although the differences vary across EV types. The lower residual values among vehicles with low mileage or young vehicle ages may partly reflect substitution toward subsidized new EVs. To examine this possibility and its implications for used-vehicle prices, we now introduce a simple model of used-vehicle pricing.

4 Pricing Model

In this section, we present a simple model of used-vehicle pricing. Let J_t denote the set of used vehicles listed for sale at time t. We assume that the price of each vehicle $j \in J_t$ is set by a monopolistic seller. Specifically, the seller that owns vehicle j at time t chooses its price to maximize the following expected profit:

$$\pi_{jt} = q_{jt}(p_{jt} - c_{jt}) + (1 - q_{jt})w_{jt}. \tag{1}$$

Here, q_{jt} denotes the probability that vehicle j is sold at time t, c_{jt} denotes the transaction cost incurred upon sale, and w_{jt} denotes the seller's discounted expected continuation value if the vehicle remains unsold, net of inventory costs. Conditional on the vehicle being listed at the beginning of

period t, its sale probability depends on its price p_{jt}, the subsidy S_{jt} available for the corresponding new vehicle, and a vector of other control variables $\mathbf{x}_{jt}$:

$$q_{jt} = \Pr(Sold_{jt} = 1 \mid p_{jt}, S_{jt}, \mathbf{x}_{jt}; \boldsymbol{\beta}) = q(p_{jt}, S_{jt}, \mathbf{x}_{jt}; \boldsymbol{\beta}),$$

where $\boldsymbol{\beta}$ denotes a parameter vector to be estimated. The specification of $q(\cdot)$ and the estimation procedure are presented in the following section.

Used vehicles generally exhibit item-specific heterogeneity in consumer valuations, which may lead sellers to incorporate dynamic considerations into their pricing decisions. As discussed in Huang, Luo, and Xia (2019), sellers may learn about consumer valuations through the selling process. In our data, however, frequent price adjustments are uncommon. This observation partly motivates our simplifying assumption that the continuation value does not depend on the current price, $\partial w_{jt}/\partial p_{jt} = 0$. Infrequent price adjustment does not, however, rule out dynamic pricing considerations, since adjustment costs may discourage price changes even when sellers learn about demand. We therefore treat this restriction as a modeling simplification rather than an implication of the observed pricing patterns.

Assuming also that c_{jt} does not depend on the current price, the first-order condition for an interior optimum of Eq. (1) yields:

$$p_{jt} = -\left(\frac{\partial q_{jt}}{\partial p_{jt}}\right)^{-1} q_{jt} + c_{jt} + w_{jt}. \tag{2}$$

The first term on the right-hand side represents the markup over the opportunity cost of selling vehicle j at time t, given by $c_{jt} + w_{jt}$.

4.1 Estimation of sale probability

We use $Sold_{jt}$ as the dependent variable and specify the sale-probability function $q(\cdot)$ in logit form as follows:

$$q(p_{jt}, S_{jt}, \mathbf{x}_{jt}; \boldsymbol{\beta}) = \frac{\exp(\beta_1 p_{jt} + \beta_2 S_{jt} + \mathbf{x}_{jt}\boldsymbol{\beta}_3)}{1 + \exp(\beta_1 p_{jt} + \beta_2 S_{jt} + \mathbf{x}_{jt}\boldsymbol{\beta}_3)} \tag{3}$$

Here, $\mathbf{x}_{jt}$ includes attributes of used vehicle j at time t, such as mileage, vehicle age, and net purchase price ($p^{new}_{jt'} - S_{jt'}$), as well as a set of fixed effects. These fixed effects are for vehicle model (e.g., LEAF), the fiscal year and calendar month at time t, and the fiscal year in which vehicle j was registered. We allow for nonlinear effects of mileage and vehicle age by including their quadratic terms, consistent with the use of nonlinear specifications in empirical analyses of used-vehicle markets (e.g., Lacetera et al. (2012)).

As is well known in the demand estimation literature (e.g., Berry, Levinsohn, and Pakes (1995)), sellers may adjust the price p_{jt} in response to unobserved attributes of used vehicle j, potentially biasing the estimated price coefficient. A standard approach to addressing this endogeneity issue is to use instrumental variables, typically cost shifters. However, cost shifters that vary across individual used vehicles are difficult to obtain; hence, we instead include variables that capture

heterogeneity across vehicles. In particular, we include net purchase price as a proxy for trim-level heterogeneity in attributes, alongside vehicle-model fixed effects (e.g., LEAF and PRIUS PHV). We also include mileage and vehicle age, two key attributes specific to used vehicles. Conditional on these variables and fixed effects, we assume that the logit error term is independent of price p_{jt}.

In the estimation, we also consider specifications that allow the coefficients on used-vehicle price (p_{jt}) and the subsidy (S_{jt}) to vary across EV types. Additionally, we estimate the models using both the full sample and a sample excluding FCVs, given the much smaller sample size for FCVs and their technological differences from other EV types, particularly their reliance on hydrogen refueling rather than electric charging.

The subsidies for new EV purchases may induce the substitution with the used EVs and thus they have negative impact on the sale probability of used vehicles. However, if the capacity constraint on new EV production exists, the increase in new vehicle sales induced by the subsidies may lengthen the delivery time, thereby increasing demand for immediately available used EVs. Therefore, the effects of subsidies can be positive or negative, and may vary across EV types.

4.1.1 Matching

As discussed in Section 3.3, EV offerings have been limited in many market segments. We therefore conduct a matching analysis before estimating the sale-probability model. The matching procedure is identical to that described in Section 3.3, except that we include vehicles regardless of whether their listings end in a recorded sale. Matching is performed using the latest observed listing for each vehicle, after which the monthly observations for the matched vehicles are used to estimate sale probabilities.

Covariate balance is summarized in Table 5. Based on the unrounded values, the absolute SMDs for all variables are below 0.10 after matching, indicating small differences in observed covariate means between EVs and HVs. The matched sample contains 13,742 distinct EVs and 27,630 distinct HVs. Further details of the matching analysis are provided in Appendix B.

4.1.2 Estimation results

Table 6 reports the estimation results based on the matched sample. Columns (1)–(3) include all vehicle types, while columns (4)–(6) exclude FCVs. The coefficients on used-vehicle prices are negative and statistically significant in all specifications, with baseline coefficients slightly below -1. As shown in columns (3) and (6), the price coefficients vary across vehicle types. The interaction terms imply that the price coefficient is less negative for BEVs and FCVs than for HVs, while it is more negative for PHVs. To interpret this heterogeneity more directly, Table 7 reports the price elasticities of sale probability, computed using the estimates in column (3) of Table 6. The mean elasticity for PHVs is -2.76, the largest in absolute value among the vehicle types, whereas BEVs and FCVs have smaller mean elasticities in absolute value than HVs. This may reflect closer substitution between PHVs and gasoline vehicles, including HVs.

Table 5: Covariate balance before and after matching: Sale-probability analysis

	Before matching				After matching			
Variable	EV	HV	Diff.	SMD	EV	HV	Diff.	SMD
Footprint (m^2)	8.13	6.98	1.15	1.12	8.13	8.11	0.02	0.03
Height (m)	1.54	1.56	-0.02	-0.23	1.54	1.55	-0.01	-0.09
Age (months)	42.47	39.55	2.91	0.11	42.47	44.83	-2.36	-0.09
Mileage (10,000 km)	2.69	2.74	-0.05	-0.02	2.69	2.97	-0.28	-0.10
Net purchase price (million yen)	3.60	2.55	1.06	1.18	3.60	3.52	0.08	0.09
No. of vehicles	13,742	336,061			13,742	27,630		

Notes: Matching is performed using the latest observed listing for each distinct vehicle, regardless of whether the listing ends in a recorded sale. The EV and HV columns report covariate means based on these latest listings, and the reported counts refer to distinct vehicles. Monthly observations for the matched vehicles are subsequently used to estimate sale probabilities, with $Sold_{jt}$ as the dependent variable. Diff. denotes the EV–HV mean difference. SMD denotes the standardized mean difference, defined as the EV–HV mean difference divided by the pooled standard deviation. Reported SMDs are rounded to two decimal places; based on the unrounded values, all absolute SMDs after matching are below 0.10.

The estimated subsidy coefficients in columns (1) and (4) of Table 6 are negative, but the coefficient is statistically insignificant in column (1) and significant only at the 10% level in column (4). Columns (2), (3), (5), and (6) reveal heterogeneity in subsidy effects across vehicle types. In particular, the subsidy coefficients for BEVs are negative and statistically significant in all specifications that allow subsidy effects to vary across vehicle types, suggesting that new and used BEVs are substitutes.

By contrast, the subsidy coefficients for PHVs are positive and statistically significant. One possible explanation is that capacity constraints on new-vehicle production lengthen delivery times when subsidies increase demand, thereby increasing demand for immediately available used vehicles. However, the coefficients are significant only at the 10% level when price sensitivity is allowed to vary across vehicle types.

The subsidy coefficients for FCVs are not statistically significant. This may reflect the limited sample size: FCVs are represented by a single model, MIRAI, and have far fewer observations than other EV types, which may make it difficult to identify the subsidy effect.

The coefficient on net purchase price is positive and statistically significant across all specifications, implying that, conditional on the used-vehicle price and other covariates, sale probability is higher for vehicles with higher net purchase prices when new. The linear coefficients on mileage and vehicle age are negative and statistically significant, consistent with the expected negative relationship between vehicle use and sale probability. The quadratic term is positive and statistically significant for mileage but insignificant for vehicle age. The positive quadratic term for mileage indicates that its negative association with the log odds of sale weakens as mileage increases, over the range in which the estimated slope remains negative.

All specifications include vehicle-model fixed effects, which absorb time-invariant differences

Table 6: Estimation results

	(A) Full Sample			(B) No FCV		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Used price(p_{jt})	-1.004***	-1.019***	-1.060***	-1.034***	-1.049***	-1.058***
	(0.027)	(0.027)	(0.031)	(0.028)	(0.028)	(0.031)
p_{jt} × BEV	-	-	0.171***	-	-	0.163***
			(0.053)			(0.053)
p_{jt} × PHV	-	-	-0.140***	-	-	-0.143***
			(0.044)			(0.044)
p_{jt} × FCV	-	-	0.264***	-	-	-
			(0.060)			
Subsidy(S_{jt})	-0.031	-	-	-0.156*	-	-
	(0.061)			(0.091)		
S_{jt} × BEV	-	-0.420***	-0.282**	-	-0.441***	-0.291**
		(0.106)	(0.114)		(0.106)	(0.114)
S_{jt} × PHV	-	0.443***	0.277*	-	0.436***	0.277*
		(0.136)	(0.144)		(0.137)	(0.145)
S_{jt} × FCV	-	0.047	0.083	-	-	-
		(0.079)	(0.080)			
Net purchase price	0.531***	0.547***	0.580***	0.541***	0.557***	0.577***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.039)
Mileage	-0.133***	-0.135***	-0.137***	-0.137***	-0.139***	-0.141***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Mileage^2	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.258***	-0.264***	-0.261***	-0.252***	-0.263***	-0.259***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Age^2	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No. of observations	106376	106376	106376	103717	103717	103717
Pseudo R^2	0.027	0.028	0.028	0.027	0.027	0.028
No. of clusters	41363	41363	41363	40487	40487	40487

Notes: Standard errors clustered at the vehicle-stock level are reported in parentheses. Used price, subsidy, and net purchase price are measured in million yen. Mileage is measured in 10,000 km, and age is measured in years. Model, fiscal-year, registration-fiscal-year, and calendar-month fixed effects are included in all specifications. HVs are included in all columns. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

across vehicle models. We therefore do not separately include vehicle attributes used in the matching analysis that vary only across vehicle models.

4.2 Counterfactual simulation

So far, we have found that subsidies may have a negative effect on the sale probability of BEVs. To translate the estimated effects on sale probabilities into implications for markups, we conduct a counterfactual simulation based on the pricing model. Specifically, using the pricing equation in Eq. (2), we compare markups under the actual subsidies with those under $S_{jt} = 0$, holding observed

Table 7: Price elasticity by vehicle type

Type	No. of observations	Mean	SD
All	106376	-2.207	0.916
BEV	15730	-1.520	0.518
PHV	18885	-2.763	0.750
FCV	2659	-1.980	1.211
HV	69102	-2.220	0.910

Notes: The table reports summary statistics for the price elasticity of sale probability, defined as $\frac{\partial q_{jt}}{\partial p_{jt}} \frac{p_{jt}}{q_{jt}}$ and computed using the estimates reported in column (3) of Table 6. No. of observations refers to vehicle-month observations. SD denotes the standard deviation.

used-vehicle prices and all other covariates fixed rather than reoptimizing prices.[8] The markup, represented by the first term in the pricing equation, can be written as follows:

$$-\left(\frac{\partial q_{jt}}{\partial p_{jt}}\right)^{-1} q_{jt} = -\frac{1}{\beta_1(1-q_{jt})}. \tag{4}$$

Using the estimates reported in column (3) of Table 6, we first derive the actual and counterfactual sale probabilities and then compute the corresponding markups using Eq. (4). In applying Eq. (4), we use the price coefficient for each vehicle type, including the corresponding interaction coefficient. Thus, differences in markups across vehicle types reflect not only differences in sale probabilities but also differences in price sensitivity.

The results of the counterfactual simulation are summarized in Table 8. Panel (I) reports the actual and counterfactual sale probabilities by vehicle type, computed using the estimates reported in column (3) of Table 6. The Difference column reports the actual sale probability minus the counterfactual sale probability and thus measures the effect of the subsidy on the sale probability. Consistent with the negative and positive estimates of the subsidy coefficients, the estimated effect is negative and statistically significant for BEVs but weakly positive for PHVs. Panel (II) reports the estimated effects on markups. The subsidy lowers the estimated markup on BEVs by approximately 34,000 yen, while raising that on PHVs by approximately 17,000 yen.

Finally, Table 9 reports estimated markups relative to net purchase prices, allowing comparison with residual values. For BEVs, the current subsidy reduces this ratio by approximately 1.1 percentage points. This magnitude is small relative to the residual value gap between BEVs and HVs discussed in Section 3, suggesting a limited contribution through the estimated markup channel. By contrast, the subsidy increases this ratio for PHVs, although the effect is merely 0.5 percentage points. The difference in subsidy effects between BEVs and PHVs is consistent with the higher

[8] A related approach in merger analysis is upward pricing pressure (UPP) test, which evaluates changes in pricing incentives at pre-merger prices without computing post-merger equilibrium prices. See Farrell and Shapiro (2010) for details.

Table 8: Counterfactual simulation: Sale probability and markup

	(I) Sale probability			(II) Markup (million yen)		
Type	Actual	Counterfactual	Difference	Actual	Counterfactual	Difference
All	0.172	0.172	-0.000 (0.002)	1.164	1.165	-0.001 (0.003)
BEV	0.144	0.165	-0.021*** (0.007)	1.320	1.354	-0.034*** (0.012)
PHV	0.163	0.149	0.014* (0.008)	1.000	0.983	0.017* (0.010)
FCV	0.158	0.135	0.024 (0.025)	1.507	1.461	0.045 (0.051)
HV	0.181	0.181	-	1.160	1.160	-

Notes: The figures are constructed using the estimates reported in column (3) of Table 6. The counterfactual sets the current subsidy to zero ($S_{jt} = 0$). Difference is calculated as the actual outcome minus the counterfactual outcome. Standard errors of the differences, computed using the delta method, are reported in parentheses. *** and * denote statistical significance at the 1% and 10% levels, respectively.

Table 9: Subsidy Effect on Markup Relative to Net Purchase Price

Type	Actual	Counterfactual	Difference
All	0.353	0.353	-0.001 (0.001)
BEV	0.415	0.426	-0.011*** (0.004)
PHV	0.276	0.271	0.005* (0.003)
FCV	0.284	0.275	0.009 (0.010)
HV	0.362	0.362	-

Notes: The table reports estimated markups relative to net purchase prices, computed using the estimates reported in column (3) of Table 6. The counterfactual sets the current subsidy to zero ($S_{jt} = 0$). Difference is calculated as the actual outcome minus the counterfactual outcome. Standard errors of the differences, computed using the delta method, are reported in parentheses. *** and * denote statistical significance at the 1% and 10% levels, respectively.

residual values of PHVs reported in Table 4, but the estimated effects explain only a part of the residual-value gap between the two EV types.

5 Conclusion

This study examines the residual values of EVs and the effects of new EV subsidies on Japan's used-vehicle market. Our preliminary matching analysis shows that EVs have lower residual values than HVs among vehicles with low mileage or young vehicle ages. Specifically, EV residual values are 10–12 percentage points lower than those of HVs in the first four quintiles of both mileage and vehicle age. These differences vary across EV types: FCVs exhibit the largest gaps relative to HVs, followed by BEVs, whereas the differences for PHVs are smaller.

We then examine the possibility that the subsidies affect the residual values through the demand

relationship between used and new vehicles. We estimate the sale probabilities of used vehicles and find that the effects of subsidies for new EVs differ across EV types. Specifically, the sale probability of used BEVs is negatively affected by the subsidy for new BEVs, suggesting that subsidies induce substitution from used to new vehicles. Based on the simple model of used-vehicle pricing, we conduct counterfactual simulations to translate the estimated subsidy effects on sale probabilities into implications for used-vehicle prices. The simulations show that subsidies reduce estimated BEV markups relative to net purchase prices by approximately 1.1 percentage points. The implied price effect through the estimated markup channel is therefore small relative to the residual value gap with HVs.

These findings suggest that, because residual values are calculated relative to purchase prices net of subsidies, consumers who replace their EVs relatively early, particularly BEVs and FCVs, incur greater depreciation costs even after accounting for purchase subsidies. Given the experience-good characteristics of EVs, uncertainty about their usability may be particularly relevant for consumers with no prior EV ownership experience. Low residual values make replacement costly if consumers find EVs less usable than expected, potentially discouraging initial purchases. This mechanism may contribute to the limited adoption of EVs in Japan, although the subsidy for new EV purchase has little impact on the residual values.

If low residual values contribute to low new-EV sales in Japan, subsidies for used EVs, such as those introduced under the US Inflation Reduction Act, may help support residual values and thereby promote new-EV sales. However, this study does not assess the effect of residual values on new-EV adoption, so evaluating this mechanism remains an important issue for future research. More generally, we have not identified the factors underlying low residual values, which also warrant further investigation.

Appendix

A New EV sales data

The new EV sales data are obtained from the fee-based automotive information platform operated by MarkLines (`https://www.marklines.com/en/`). The platform provides new vehicle sales data by powertrain, including BEVs, PHVs, FCVs, and HVs. The countries and regions covered by the EV sales data used in this study are listed in Table A1.

B Detail of Matching Analysis

We conduct separate matching analyses for the preliminary analysis of residual values and the analysis of sale probabilities. For the residual-value analysis, we use the last observed listing for each vehicle recorded as sold. For the sale-probability analysis, we use the latest observed listing for each vehicle, regardless of whether the listing ends in a recorded sale. Each vehicle contributes

one observation to the matching sample. Before matching, the former sample contains 5,766 EVs and 146,283 HVs, while the latter contains 13,742 EVs and 336,061 HVs. For the sale-probability analysis, we subsequently use the monthly observations for the matched vehicles rather than only their latest listings.

For each sample, we estimate the following linear probability model by ordinary least squares:

$$\mathrm{EV}_j = \alpha_0 + \mathbf{z}_j'\boldsymbol{\alpha} + \varepsilon_j, \tag{5}$$

where EV_j equals one for an EV (BEV, PHV, or FCV) and zero for an HV. The vector $\mathbf{z}_j$ contains footprint, height, vehicle age, mileage, and net purchase price. Footprint is vehicle length multiplied by width and is measured in square meters; height is measured in meters. Vehicle age is the time elapsed since initial registration, expressed in years, and mileage is the odometer reading, expressed in units of 10,000 km. Net purchase price is the corresponding new-vehicle list price minus the subsidy available at initial registration, expressed in million yen. Vehicle age and mileage are measured at the listing selected for each matching sample.

Table B1 reports the estimation results. In both samples, footprint, height, vehicle age, and net purchase price are positively associated with the EV indicator, whereas mileage is negatively associated with it. We use the fitted values as propensity scores and match each EV to three nearest-neighbor HVs. Figure B1 compares the distributions of these scores for EVs and HVs before matching.

The score distributions overlap in both samples, and the entire range of estimated scores for EVs lies within the corresponding range for HVs. Thus, the empirical common-support requirement for matching EVs to HVs is satisfied in terms of the observed score ranges. Some fitted values are negative because the linear probability model does not constrain its predictions to the unit interval. This may be problematic because propensity scores represent probabilities. However, our objective in the matching analyses is to construct comparable groups of EVs and HVs, rather than to predict EV status accurately; we assess the suitability of the scores primarily through post-matching covariate balance.

We also estimated a logit model to obtain propensity scores constrained to the unit interval.

Table A1: Countries and regions covered by the EV sales data

Argentina	Colombia	Greece	Kazakhstan	Norway	Saudi Arabia	Thailand
Australia	Croatia	Hungary	Korea	Oman	Singapore	Turkey
Austria	Czech Republic	India	Kuwait	Pakistan	Slovakia	UAE
Belgium	Denmark	Indonesia	Luxembourg	Peru	Slovenia	UK
Brazil	Egypt	Iran	Malaysia	Philippines	South Africa	USA
Bulgaria	Estonia	Ireland	Mexico	Poland	Spain	Ukraine
Canada	Finland	Israel	Myanmar	Portugal	Sweden	Uruguay
Chile	France	Italy	Netherlands	Romania	Switzerland	Vietnam
China	Germany	Japan	New Zealand	Russia	Taiwan	

Notes: The table lists the 62 countries and regions covered by the EV sales data used in this study.

Table B1: Propensity Score Estimation for the Matching Analyses

Variable	(1) Residual-value analysis	(2) Sale-probability analysis
Footprint	0.0238***	0.0259***
	(0.0008)	(0.0005)
Height	0.2014***	0.2239***
	(0.0070)	(0.0047)
Age	0.0012***	0.0024***
	(0.0003)	(0.0002)
Mileage	−0.0043***	−0.0048***
	(0.0003)	(0.0002)
Net purchase price	0.0171***	0.0176***
	(0.0007)	(0.0005)
Constant	−0.4810***	−0.5323***
	(0.0143)	(0.0095)
No. of vehicles	152,049	349,803
EVs	5,766	13,742
HVs	146,283	336,061
R^2	0.0397	0.0444

Notes: The dependent variable equals one for EVs and zero for HVs. Both columns report linear probability models estimated before matching. Conventional OLS standard errors are in parentheses; *** denotes significance at the 1% level. Footprint is measured in square meters, height in meters, vehicle age in years, odometer reading in 10,000 km, and net purchase price in million yen. Column (1) uses vehicles recorded as sold. Column (2) uses the latest observed listing for each vehicle, regardless of whether the listing ends in a recorded sale. Each vehicle contributes one observation. Neither specification includes fixed effects or quadratic terms.

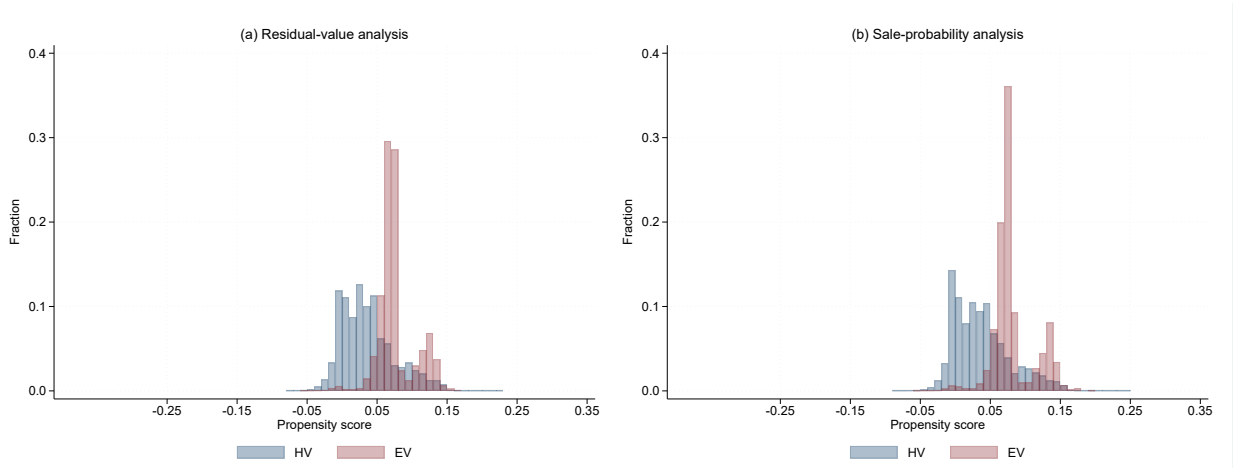


Figure B1: Propensity Score Distributions Before Matching

Notes: Panels (a) and (b) correspond to columns (1) and (2) of Table B1, respectively. Histograms show the fractions of vehicles within each group, using a common bin width of 0.01. EVs include BEVs, PHVs, and FCVs. The scores are fitted values from linear probability models and may lie outside the unit interval.

However, this alternative did not improve covariate balance overall. Specifically, in the residual-value sample, the absolute post-matching SMDs for height and vehicle age were 0.215 and 0.115 under the

logit model, compared with 0.054 and 0.085 under the linear probability model. Although the logit model slightly reduced the absolute SMD for mileage, from 0.139 to 0.126, this improvement came at the cost of greater imbalance in height and vehicle age. We therefore retain the linear probability model as our baseline matching specification.

References

Allcott, Hunt, Reigner Kane, Maximilian S. Maydanchik, Joseph S. Shapiro, and Felix Tintelnot. 2026. "The Effects of "Buy American": Electric Vehicles and the Inflation Reduction Act." *NBER Working Paper No. 33032*.

Allcott, Hunt, Hyuk-soo Kwon, and Tess Snyder. 2024. "Equitable Energy Transitions? The Efficiency and Distributional Effects of Subsidies for Used Electric Vehicles." *Working Paper*.

Austin, Peter C. 2009. "Balance Diagnostics for Comparing the Distribution of Baseline Covariates between Treatment Groups in Propensity Score Matched Samples." *Statistics in Medicine* 28 (25):3083–3107.

Barwick, Panle Jia, Hyuk-soo Kwon, and Shanjun Li. 2024. "Attribute-based Subsidies and Market Power: an Application to Electric Vehicles." *Working Paper*.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4):841–890.

Bushnell, James B., Erich Muehlegger, and David S. Rapson. 2022. "Energy Prices and Electric Vehicle Adoption." *NBER Working Paper No. 29842*.

Davis, Lucas W., Jing Li, and Katalin Springel. 2026. "Political Ideology and U.S. Electric Vehicle Adoption." *Journal of the Association of Environmental Resource Economists* 13 (5):1337–1351.

Dorsey, Jackson, Ashley Langer, and Shaun McRae. 2025. "Fueling Alternatives: Gas Station Choice and the Implications for Electric Charging." *American Economic Journal: Economic Policy* 17 (1):362–440.

Farrell, Joseph, and Carl Shapiro. 2010. "Antitrust Evaluation of Horizontal Mergers: An Economic Alternative to Market Definition." *The B.E. Journal of Theoretical Economics* 10 (1).

Fournel, Jean-François. 2025. "Electric Vehicle Subsidies: Cost-Effectiveness and Emission Reductions." *Working Paper*.

Gillingham, Kenneth T., Matthew Kotchen, James A. Levinsohn, and Barry J. Nalebuff. 2025. "The Musk Partisan Effect on Tesla Sales." *NBER Working Paper No. 34413*.

Gillingham, Kenneth, Marten Ovaere, and Stephanie M. Weber. 2021. "Carbon Policy and the Emissions Implications of Electric Vehicles." *NBER Working Paper No. 28620*.

Gillingham, Kenneth T., Arthur A. van Benthem, Stephanie Weber, Mohamed Ali Saafi, and Xin He. 2023. "Has Consumer Acceptance of Electric Vehicles Been Increasing? Evidence from Microdata on Every New Vehicle Sale in the United States." *AEA Papers and Proceedings* 113:329–335.

Huang, Guofang, Hong Luo, and Jing Xia. 2019. "Invest in Information or Wing It? A Model of Dynamic Pricing with Seller Learning." *Management Science* 65 (12): 5556–5583.

International Energy Agency (IEA). 2025. *World Energy Outlook 2025*. Paris: International Energy Agency.

Ito, Koichiro and James M. Sallee. 2018. "The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel Economy Standards." *Review of Economics and Statistics* 100 (2):319–336.

Kitano, Taiju. 2022. "Environmental Policy as de facto Industrial Policy: Evidence from the Japanese Car Market." *Review of Industrial Organization* 60:511–548.

Kitano, Taiju. 2025. "Greening Vehicle Fleet: A Structural Analysis of Scrappage Programs during the Financial Crisis." *International Journal of Industrial Organization* 103 Part B:103203.

Konishi, Yoshifumi and Shunsuke Managi. 2020. "Do Regulatory Loopholes Distort Technical Change? Evidence from New Vehicle Launches under the Japanese Fuel Economy Regulation." *Journal of Environmental Economics and Management* 104:102377.

Konishi, Yoshifumi and Meng Zhao. 2017. "Can Green Car Taxes Restore Efficiency? Evidence from the Japanese New Car Market." *Journal of the Association of Resource and Environmental Economists* 4 (1): 51-87.

Lacetera, Nicola, Devin G. Pope, and Justin R. Sydnor. 2012. "Heuristic Thinking and Limited Attention in the Car Market." *American Economic Review*, 102(5): 2206–2236.

Li, Jing. 2023. "Compatibility and Investment in the U.S. Electric Vehicle Market." *Working Paper*.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. "The Market for Electric Vehicles: Indirect Network Effects and Policy Design." *Journal of the Association of Environmental and Resource Economists* 4 (1):89–133.

Muehlegger, Erich and David S. Rapson. 2022. "Subsidizing Low- and Middle-Income Adoption of Electric Vehicles: Quasi-experimental Evidence from California." *Journal of Public Economics* 216: 104752.

Remmy, Kevin. 2026. "Adjustable Product Attributes, Indirect Network Effects, and Subsidy Design: The Case of Electric Vehicles." *American Economic Journal: Economic Policy* 18 (2):107–140.

Springel, Katalin. 2021. "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives." *American Economic Journal: Economic Policy* 13 (4):393–432.

Sunada, Takeaki and Tianli Xia. 2026. "From Pumps to Plugs: Value of Time and Charging Policies." *Working Paper*.

Tebbe, Sebastian. 2025. "Peer Effects in Electric Car Adoption: Evidence from Sweden." *Working Paper*.

Zhou, Yiyi and Shanjun Li. 2018. "Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market." *Journal of Industrial Economics* 66 (2):423–480.