The market for used battery electric vehicles – a viable mechanism for providing access to a new vehicle propulsion technology?

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Motivation

- Policy goal: reduce GHG emissions from transportation sector.
- Approach: Incentivize the switch to electric propulsion.
  - Policies (at federal and state level) support purchase of new battery electric vehicles (BEVs).
  - Yet, a new BEV is significantly more expensive than the average new car [$64k vs $44k].
- What role does the used vehicle market play in the diffusion of the new technology?
  - Note: Volume in used car market is 2.5 to 3 times that of new vehicle market; potential to be an effective transmission mechanism.
- Research on the used BEV market is scant. Previous research on the economics of BEVs has focused on evaluating policy design for BEV adoption, measuring vehicle miles traveled of BEVs, and estimating environmental effects of BEV adoption (Muehlegger & Rapson (2021), Davis (2019), Holland et al (2016)).

Our Paper

- Question: What does the market for used BEVs look like relative to that of vehicles with other propulsion technology (e.g. internal combustion engine, hybrids, others)?
- **Main finding: BEVs enter the used vehicle market at the slowest rate compared to vehicles of other powertrains.**
- Why? Today, we will highlight some possible supply-side explanations.
  1. Lower usage of BEVs $\Rightarrow$ puts downward pressure on potential supply of used BEVs.
  2. For vehicles with a more modern vintage, featuring batteries with much improved range, we find the usage effect to fade in importance.
  3. Finding in (1) carries through across different regional geographies.

Data Sources

- Experian Automotive's Autocount database:
  - Universe of non-fleet vehicle registrations in the U.S., sourced from DMV title and registration data.
  - Includes data on make, model, model year (MY), odometer reading, registration date (month/year), new or used indicator, and owner zip code of all vehicle registrations.
- Wards Intelligence data center:
  - Provides information on powertrain and segment of vehicle by make-model-MY.
- U.S. Department of Energy:
  - Covers information on the battery range (in miles) of BEVs in our data at the make-model-MY level.

Data Restrictions and Matching

- We restrict our dataset to include all registrations of MY2010 to MY2022. We do this to anchor the analysis to the beginning of mass market BEV sales in the U.S. This starts us with 289 million registrations filed from January 2009 to December 2022.
  - 2010 Nissan Leaf is the first BEV to be produced for the mass market from a major manufacturer.
- Merge the Wards data on make-model-MY to the Autocount data. The match rate is 96.4%.
- Our data does not provide VIN numbers, making it impossible to track vehicles from owner to owner. As a result, we collapse our data into a panel where the unit of observation is *product-age*.

Panel Creation and Unit of Observation

- A *product* is a make-model-MY [Toyota-Corolla-2011] and *age* is the difference between year of registration t and model year v. A product with registrations in 2012 with a 2010 model year is 2 years old.
- For each product-age we observe: the total number of new registrations, total number of used registrations, segment, powertrain bucket, and the mean odometer reading for the used registrations.
- Each observation falls into one of four mutually exclusive powertrain buckets:
  - **ICE**: diesel, gas, or natural gas
  - **Hybrid**: traditional hybrids and plug-in hybrids
  - **BEV**: electricity exclusively
  - **Mixed**: products that are a mix of power types (e.g., 2020 Ford Fusion gasoline or hybrid)

Product and Registration Tabulation

Table: Sum and Share of Product-Age Observations and the Registrations they Represent

Bucket	New Registrations	Used Registrations	Product-Age N
ICE	103,065,493	95,298,461	21,022
	(69.8%)	(72.6%)	(81.3%)
Mixed	40,920,154	34,242,655	3,689
	(27.7%)	(26.1%)	(14.3%)
Hybrid	2,082,797	1,349,113	697
	(1.4%)	(1.0%)	(2.7%)
BEV	1,667,704	352,705	442
	(1.1%)	(0.3%)	(1.7%)
Total	147,736,144	131,242,936	25,850

Modelling the Used Vehicle Market: Used Prevalence Ratio

- We model the used market for a given product by calculating the cumulative number of used registrations of product *vbm* (model year *v*, make *b*, model *m*) at age *a* divided by the total number of new registrations of that product ever.

$$\text{UPR}_{vbma} = \frac{\sum_a ur_{vbma}}{nr_{vbm}} \mid a = t - v \quad (1)$$

- Allows us to map the used market of a product over its lifetime. Approximately the percentage of registrations of a product that have been ”absorbed” by the used market.
- It is possible for the UPR to surpass 1 because we are observing ”new to used” transactions and ”used to used” transactions.
- We focus the analysis on product-age observations from ages 1 to 9. We anchor to age 1 to provide some time for the used vehicle market of a given product to develop and stop the analysis at age 9 as vehicles that go beyond that age represent few used registrations in our data.

Used Prevalence Ratio

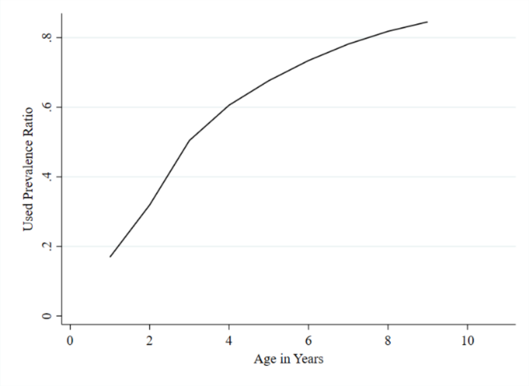
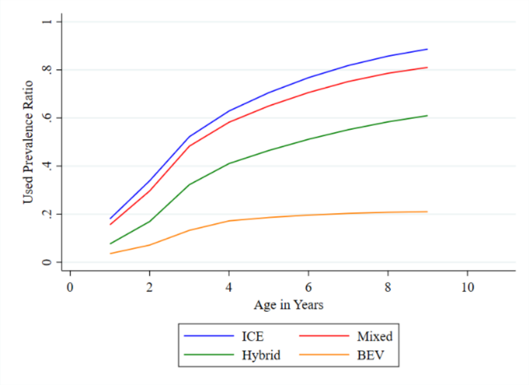


Figure: This is the pooled used prevalence ratio across all products in the dataset. We sum all used and new registrations by age, and perform the calculation from the UPR equation.

Stylized fact: BEVs enter used market at slowest rate



Effects of Powertrain Bucket on UPR

- We begin by modelling the relationship between powertrain bucket and the UPR for all relevant observations in our dataset. We estimate the following equation:

$$y_{vbma} = \alpha_{ab} + \alpha_{at} + \alpha_{vbma} + \beta_1 powertrain_{vbm} + \epsilon \tag{2}$$

- y_{vbma} is the UPR of product *vbm* at age *a*,
- α_{ab} are age-make fixed effects,
- α_{at} are age-year (of registration) fixed effects,
- α_{vbma} are age-segment fixed effects, and
- $powertrain_{vbm}$ is the powertrain bucket of product *vbm*.
- We estimate by OLS, cluster standard errors at the make-model-age level, and weight by the total number of new registrations of each product.

Main Result: BEVs transition to used more slowly

Table: Coefficient Estimates of Equation (2)

	(1) Equation (2)
BEV	**-35.657*****
	(2.868)
Hybrid	-25.795***
	(1.790))
Mixed	-4.257***
	(0.805)
Observations	17,852
Adjusted R^2	0.222

* $p < .1$, ** $p < .05$, *** $p < .01$
Standard errors in parentheses

Why do BEVs transition to used slower than ICE vehicles?

- Lower usage (debated), which could be caused by a number of mechanisms:
  - Range anxiety- the fear of the driver that their BEV does not have sufficient charge to complete a trip
  - Lack of a charging network
  - Geography- perhaps individuals who purchase BEVs drive less
- Technology improvements- consumers are delaying BEV purchases due to the fact that the technology improves every model year.
- Depreciation- evidence that BEVs depreciate faster than ICE vehicles (Guo & Zhou (2018)).
- In the rest of our analysis, we dive more into the vehicle miles traveled debate as a possible explanation.

BEVs are driven significantly less than others

- There is active debate amongst researchers about the vehicle miles traveled of BEVs (Burlig et al (2019), Davis (2019)). Much of this debate comes from the fact that it is difficult to directly measure.
- We proxy vehicle miles traveled (VMT) with the mean odometer reading of all used registrations of each product-age observation in our dataset. This comes directly from the registration data.

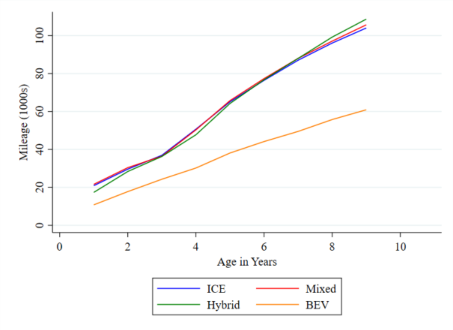


Figure: Average Used Odometer Reading over Age, by Bucket

Accounting for VMT in our Model

- We account for the variation in usage by utilizing a similar econometric framework to Equation (2):

$$y_{vbma} = \alpha_{ab} + \alpha_{at} + \alpha_{vbma} + VMT_{vbma} + \beta_1 powertrain_{vbm} + \epsilon \quad (3)$$

where the only difference between Equation (3) and (2) is that we add a term for the VMT of each product *vbm* at age *a*.

Accounting for VMT takes away difference between BEVs and ICEs

Table: Coefficient Estimates of Equation (2) and (3)

	(1) Equation (2)	(2) Equation (3)
BEV	**-35.657*****	**0.897**
	(2.868)	(4.628)
Hybrid	-25.795***	-29.847***
	(1.790)	(2.431)
Mixed	-4.257***	-2.708***
	(0.805)	(0.770)
VMT Control?	No	Yes
Observations	17,852	17,822
Adjusted R^2	0.222	0.228

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors in parentheses

But what about technological improvements?

- One implication of our findings could be that technological improvements in the battery range of BEVs would erode the difference in VMT we are observing in the aggregate between BEVs and vehicles of other powertrains.
- It seems likely that the way battery technology developed influenced the consumption choices of individuals considering the purchase of a (new or used) BEV. Why would you purchase a BEV now if you know the range will improve by 50 miles next MY?
- Early BEV Adopters: relatively fewer product options to choose from and the technology is in its infancy.
- Late BEV Adopters: more product options and improved technology.

VMT of BEVs still low despite range improvements

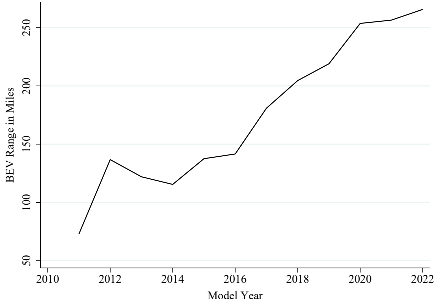


Figure: Average range of BEVs by MY

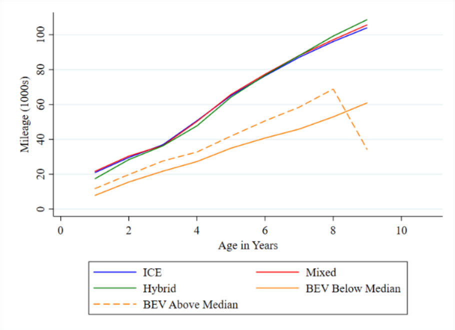


Figure: Average VMT of BEVs above and below median battery range (about 230 miles)

Modelling Effects of Technology Improvements and Early Adopters

- We can model the effects of improvements in the battery range of BEVs by distinguishing between the early adopters and late adopters of the technology.
- Early Adopters: products of MY2010-MY2015
- Late Adopters: products of MY2016-MY2022
- We re-estimate Equations (2) and (3) on these subsets of our data for products of age 1 to 5. We do this as the late adopter products have a max age of 6.

VMT better explains gap for early adopters

Table: Coefficient Estimates of Equation (2) and (3) for Early and Late Adopters

	(1) Early Adopters Equation (2)	(2) Early Adopters Equation (3)	(3) Late Adopters Equation (2)	(4) Late Adopters Equation 3
BEV	**-27.668*****	**5.446**	**-32.412*****	**-10.439*****
	(3.003)	(5.293)	(3.591)	(3.311)
Hybrid	-21.054***	-23.156***	-24.062***	-17.329***
	(2.048)	(2.583)	(2.901)	(3.139)
Mixed	-5.208***	-3.735***	-3.274***	-0.878***
	(1.312)	(1.211)	(0.740)	(0.738)
VMT Control?	No	Yes	No	Yes
Observations	7,422	7,404	5,165	5,153
Adjusted R^2	0.160	0.167	0.459	0.485

* $p < .1$, ** $p < .05$, *** $p < .01$
Standard errors in parentheses

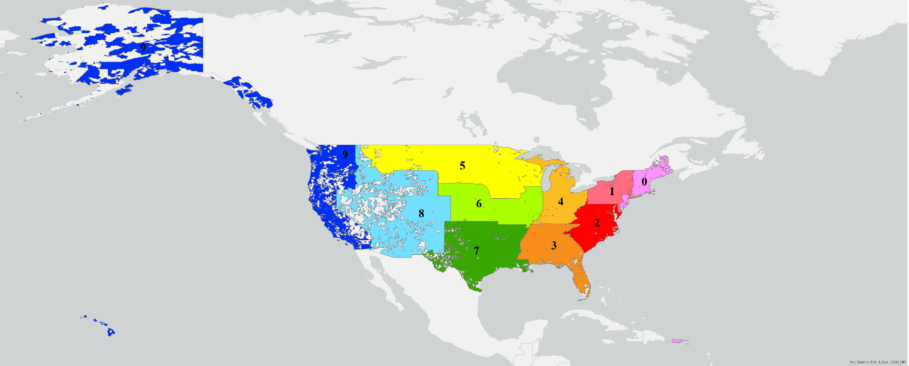
Addressing Self-Selection: Geography

- A possible concern regarding our findings could be that BEVs are getting sorted into zip codes in which individuals drive less than the average vehicle owner.
- We know that BEV ownership is positively correlated with household income, education level, and population density.
- We can investigate this as our registration data tells us the owner zip code of each vehicle registration.

Addressing Self-Selection: Geography

- We add a geographic level to our unit of observation such that an observation is now geography-product-age.
- The geographic component is a Zip Code Tabulation Area (ZCTA)- a 5-digit generalized representation of a zip code created by the Census. This represents the ZCTA code of the owners of the registered vehicles.
- We aggregate all 5-digit ZCTAs to 1-digit ZCTAs, which essentially breaks up the geographic component into a set of 10 regions in the US.
- Our formal unit of observation: owner 1-digit ZCTA-product-age

1-Digit ZCTA Map



Addressing Self-Selection: Geography

- We estimate the following equations:

$$y_{zvbma} = \alpha_{az} + \alpha_{ab} + \alpha_{at} + \alpha_{vbma} + \beta_1 powertrain_{vbm} + \epsilon \tag{4}$$

$$y_{zvbma} = \alpha_{az} + \alpha_{ab} + \alpha_{at} + \alpha_{vbma} + VMT_{zvbma} + \beta_1 powertrain_{vbm} + \epsilon \tag{5}$$

- Same as previous equations, but:
- y_{zvbma} is the UPR of product *vbm* at age *a* in ZCTA *z*
- VMT_{zvbma} is the VMT of product *vbm* at age *a* in ZCTA *z*
- α_{az} are ZCTA-age fixed effects
- Assumption to Equation (5): since we are proxying VMT by used odometer reading, we assume the owners of a given vehicle all live in the same 1-Digit ZCTA. More likely for 1-Digit ZCTA, not for 2-, 3-, 4-, or 5-Digit ZCTA.

Correlation at the national level carries through across geography

Table: Coefficient Estimates of Equation (4) and (5)

	(1) Equation (4)	(2) Equation (5)
BEV	**-33.185*****	**-12.302*****
	(2.350)	(3.307)
Hybrid	-27.916***	-29.675***
	(1.951)	(2.399)
Mixed	-3.648***	-2.603***
	(0.859)	(0.814)
VMT Control?	No	Yes
Observations	131,662	131,413
Adjusted R^2	0.195	0.198

* $p < .1$, ** $p < .05$, *** $p < .01$

Standard errors in parentheses

Conclusion

We have outlined a number of stylized facts with respect to the used BEV market:

1. New BEV ownership spells are longer, and thus transition to used at the slowest rate compared to ICE, hybrid, and mixed vehicles.
2. BEVs are used significantly less than ICE, hybrid, and mixed vehicles. Puts downward pressure on supply of used BEVs.
3. VMT effect fades for vehicles with more modern vintage, and better technology.
4. Correlation from (1) carries through across geography (broadly).

As it stands currently, the used BEV market is not a good mechanism for mass adoption of the technology. More research in the space needed to get at causality.