Model Offerings and Electric Vehicle Adoption

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Governments around the world are rallying behind decarbonization efforts through a suite of policies, including those that promote the adoption of electric vehicles (EVs). As a result, EV adoption has increased substantially over the past decade. In the United States, EVs achieved a 9 percent new vehicle market share in 2023, up from 2 percent just a few years prior. This rapid growth raises critical questions about consumer demand for EVs. Namely, what caused this growth, and what growth can we expect moving forward? The literature has identified several factors that increase EV demand, such as charging infrastructure and subsidies (Cole et al. 2023). We add to this literature by empirically analyzing another potentially relevant factor: new vehicle model offerings.

Research questions

Our key research question is, how important is the variety of vehicle models of alternative fuel types offered for sale in the new vehicle market for EV adoption? Specifically, our goal is to empirically measure by how much new EV sales increase in response to the introduction of EV models and the discontinuation of gasoline vehicle models in the new vehicle market. A secondary goal is to explore how estimated elasticities vary with vehicle attributes, including price, range, and body style. With measurements of these relationships in hand, we will then analyze how future new EV sales will be affected by possible future trajectories of EV and gasoline vehicle model offerings in the new vehicle market.

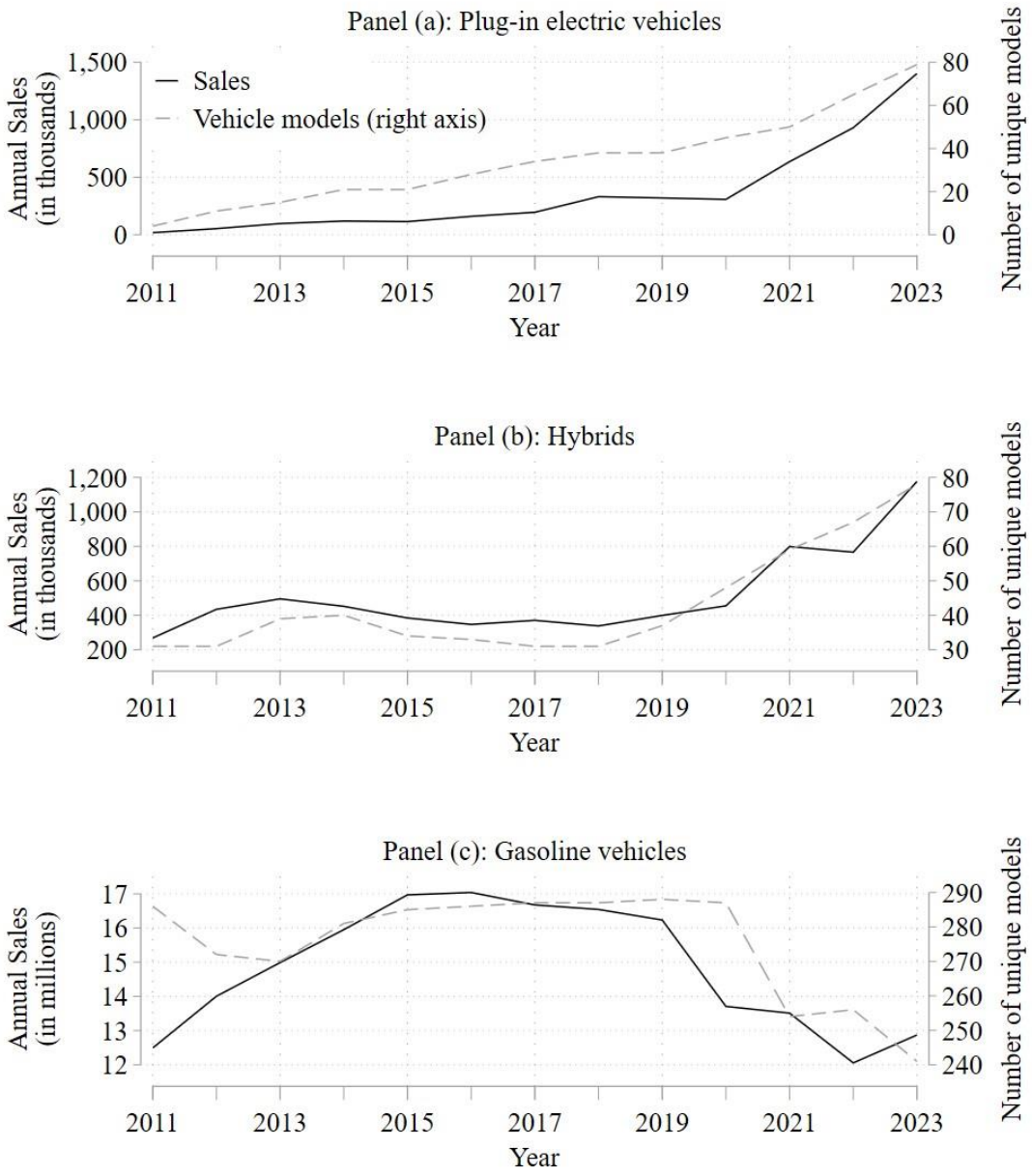
Data and methods

We use several datasets for our analysis. The first dataset is the Environmental Protection Agency (EPA) fuel economy database. These data provide us with a panel of the number of unique models available for sale in the new vehicle market. For example, the Tesla Model 3 is one unique model available for sale in 2018 that appears in the EPA database. We aggregate the data by fuel type (i.e., gasoline, hybrid, PEV) and year to count the number of unique models available for sale in the new vehicle market each year for 2011-2023.

The second dataset is a panel of aggregate new vehicle sales by fuel type and month available through Argonne National Laboratory. We aggregate these data to fuel type and year for years 2011-2023.

We merge these datasets and present motivation for our analysis in Figure 1. The figure plots new vehicle sales along with the number of unique models offered for sale in the new vehicle market, with each panel representing a different fuel type. Panel (a) shows that the number of unique EV models (including plug-in hybrids and battery EVs) offered for sale in the new vehicle market has increased substantially since 2011. Each panel shows a strong, positive correlation between sales and model offerings.

Figure 1. New vehicle sales and the number of unique models offered for sale in the new vehicle market by fuel type, 2011-2023



The third dataset is several waves of proprietary household survey data administered by Ipsos (formerly InMoment) collected from the New Vehicle Customer Survey (NVCS). The NVCS data has approximately 200,000 responses of new vehicle buyers and lessees in each annual wave. In the data, we use information on vehicles purchased or leased (including make, model, fuel type) and information on "second choice" vehicles that were most seriously considered but not purchased or leased. We use four waves of the NVCS: 2017, 2018, 2019, and 2020. These waves include significant model entry and exit that we use to identify parameters of interest.

We have two methods for estimating the relationships between EV model entry, gasoline model exit, and sales. For the first method, we rely on aggregate panel data as shown in Figure 1. We estimate the following log-share relationship:

$$\ln(s_{ft}) - \ln(s_{0t}) = \alpha + \beta_{ff} \ln(m_{ft}) + \sum_{g \neq f} \beta_{fg} \ln(m_{gt}) + \gamma X_{ft} + \varepsilon_{ft}.$$

The variables have the following definitions:

- s_{ft}: the sales share of fuel type f in year t
- s_{0t}: the sales share of the outside option in year t
- m_{ft}: the number of unique vehicle models available for sale in the new vehicle market that are of fuel type f in year t.
- m_{gt}: the number of unique vehicle models available for sale in the new vehicle market that are of fuel type g (excluding fuel type f) in year t.
- X_{ft}: a vector of control variables that explain the probability that a consumer buys a new vehicle of fuel type f, such as charging station infrastructure density.

The coefficients of interest are β_{ff} and β_{fg}, which represent how the sales of fuel type f are influenced by model entry or exit of the same fuel type vehicles and different fuel type vehicles. For this method, given our small sample size, we do not differentiate marginal effects by model entry and exit.

For the second method, we use the micro data from the NVCS waves. Here we estimate the marginal effect of a single new EV model entering the new vehicle market or a single gasoline vehicle no longer being offered for sale on aggregate EV sales. We estimate this effect one vehicle model at a time. For example, in 2018, Tesla launched the Model 3, and total EV sales increased significantly. Our method estimates counterfactual EV sales had Tesla not released the Model 3 that year. We then take the difference between observed EV sales and counterfactual EV sales to identify the sales effect of a single EV model entering the market.

The NVCS second choice data play a key role in our estimation. The data represent a plausible choice that buyers and lessees would have made had their actual selection not been available. From these data, we construct model by fuel type diversion fractions (Bordley 1993, Leard 2022), which represent the fraction of sales diverted from a model to other models that share the same fuel type as purchased or leased model. We then apply the diversion fractions to assign counterfactual sales to other EV models, which enters into a calculation of counterfactual sales.

To further explain our method, consider, for example, the entry of the Tesla Model 3 in 2018. The Model 3 had approximately 138,000 sales in 2018, and total EV sales that year were 360,273. A naïve and inaccurate approach to calculating counterfactual EV sales would be to simply subtract Model 3 sales from total EV sales. This calculation would be inaccurate because some Model 3 buyers would have chosen an alternative EV had the Model 3 not entered the market in 2018, which reduces the effect of the Model 3 entry on total EV sales. We quantify how many Model 3 buyers/lessees would have chosen an alternative EV using the NVCS second choice data. According to the data, 58 percent of Model 3 buyers/lessees stated that they had seriously considered a different EV as a second option, and 42 percent stated that they had considered a different gasoline or hybrid vehicle as a second option. Therefore, 58 percent of the 138,000 Model 3 sales, or 80,400 sales, would plausibly have been a different EV without the Model 3 being available. Therefore, our method implies that the Model 3 entry increased total EV sales by 42 percent of 138,000, or 57,960 sales.

Our plan is to first compute counterfactual total EV sales for all EV models that entered the new vehicle market during 2017-2020, as well as counterfactual EV sales for all gasoline vehicle models that exited the new vehicle market during this period. Then we quantify entry and exit elasticities as the percentage change in total EV sales in response to a one percent increase in the number of EV models offered and in response to a one percent decrease in the number of gasoline vehicle models offered. Since some EV models are especially popular, we anticipate exploring relationships between estimated elasticities and vehicle attributes, such as price and battery range.

With estimates in hand, we will perform out-of-sample prediction validation exercises by calibrating a discrete choice model of new vehicle demand to match our estimated elasticities. One validation exercise will be to compare observed national EV sales during 2021-2023 with total EV sales predicted with our discrete choice model. We will then assess how certain manufacturer statements of discontinuing gasoline vehicle models by 2035, such as those made by General Motors, can be expected to affect overall EV sales.

Our two methods have strengths and weaknesses. Our aggregate panel data approach has a strength of being based on actual sales data. However, its key weakness is that we do not measure some factors that influence EV adoption, such as the evolution of social attitudes toward EVs, which could be correlated with the number of models. Our micro second choice data approach has the strength of controlling for time-varying unobservable characteristics that influence the demand for EVs. Its key weakness is that it is dependent on stated considerations in survey responses for creating counterfactual sales. However, each method's strengths together provide a more compelling message and comprehensive analysis of the effect of model entry and exit on EV sales.

Composition of the research team

Benjamin Leard, Ph.D. is an assistant professor with a joint appointment in the Department of Agricultural and Resource Economics and The Baker School of Public Policy & Public Affairs at the University of Tennessee and a university fellow at Resources for the Future. Leard actively

publishes papers on the economics of the transportation sector in general interest economics journals and top field journals. Prior to becoming faculty at the University of Tennessee, Leard was a fellow at Resources for the Future, where he contributed to modeling effects of tightening fuel economy and greenhouse gas standards.

Hiroshi Matsushima, Ph.D. is a Research Fellow (assistant professor equivalent) at the Crawford School of Public Policy at the Australian National University. His academic work has been focused on the effectiveness of the fuel economy and tailpipe emissions standards. In his prior role as an Economic Fellow at the Institute for Policy Integrity at New York University School of Law, he undertook a thorough analysis of the most recent proposal of Corporate Average Fuel Economy (CAFE) standards and submitted detailed comments aiming to refine arguments made by the Department of Transportation (DOT).

Conflict of interest statement

Benjamin Leard and Hiroshi Matsushima do not have financial or other interests of the research team that might bear on the proposed work. Neither team member has financial or other ties to the transportation industry.

Statement regarding informing issues of interest to the Department of Transportation

Our results inform several issues of interest to DOT. The first issue will inform motor fuel tax declines associated with EV adoption. The rate of EV adoption influences the amount of motor fuel tax collected since EV owners do not pay gasoline taxes when refueling their EVs. Our study will contribute to better understanding how quickly the motor fuel tax may decline as more EVs are adopted. The second issue concerns the role that EVs play in the environmental impact statement for changes to CAFE standards. Our analysis will provide a better understanding of what factors cause increases in EV sales, which will affect how manufacturers comply with CAFE standards and the environmental effects associated with the standards. A third issue is the harmonization of CAFE standards with EPA greenhouse gas (GHG) standards for passenger cars and light trucks. The EPA directly considers EVs in setting GHG standards and the executive branch of the federal government has pushed to have the stringency of these standards harmonized with CAFE standard stringency. Our study can help inform DOT how to harmonize its standards with EPA standards as EVs gain market share.

References

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