Charged and Almost Ready—

What Is Holding Back the Resale Market for Battery Electric Vehicles?

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Abstract

We utilize vehicle registration microdata for all new and used vehicles registered in the U.S. for model years 2010-2022 to study the market for used battery electric vehicles (BEVs). From these records, we establish two stylized facts: 1) BEVs enter the used market at the slowest rate compared to any other powertrain technology, and 2) BEVs are driven significantly less than vehicles featuring other powertrain technologies. We connect these facts through a statistical model of used vehicle registration counts and find that there are significant behavioral differences between BEV and other new vehicle owners in how utilization (both on average and at the margin) leads to these vehicles being resold. By way of a counterfactual exercise that equalizes average vehicle miles traveled, we then illustrate that these behavioral differences can explain from 10-30 percent of the differential rates of transition from new to used vehicle status we observe between BEVs and internal combustion engine (ICE) vehicles.

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1. Introduction

The auto industry is facing a paradigm shift away from internal combustion engine (ICE) technology toward vehicles powered by electric batteries. While there are environmental reasons to welcome this technological change (see, for example, Tabuchi and Blumer, 2021), notably the possible reduction of greenhouse gas (GHG) emissions, economic factors will ultimately influence the new technology's rate of diffusion. In that context, it is worth noting that the average price of a new battery electric vehicle (BEV) is significantly higher than that of a vehicle powered by conventional ICE technology (Ewing, 2022). Lower affordability of new BEVs, thus, suggests a potentially outsized role of the market for used vehicles in their rate of adoption by consumers.

In fact, the resale market plays a crucial role in broadening the availability of *all* vehicles to consumers. In the U.S. in a typical year, 2.5 to 3 times as many used vehicles compared to new ones are sold (Bureau of Transportation Statistics) and used car price dispersion is approximately five times as large as that of new cars (Gavazza et al, 2014). With just under 2.3 million new BEVs sold in the U.S. from 2010 through 2022, representing a mere 1.1% of new vehicle sales over that period, the resale market for BEVs is considerably smaller than that for ICE vehicles.[1] As the share of BEVs among new vehicle sales is projected to rise[2], the market for used BEVs is expected to grow commensurately in size. Industry analysts are counting on this fact to play an important role in increasing the adoption of this new propulsion technology.

In this paper we take a closer look at what might be holding back progress on this front. Given the slow rate of adoption in many countries, governments around the world have put in place financial incentives designed to speed up the adoption of BEVs. While many of these policies have focused solely on incentives supporting the sale of new BEVs, in the U.S. context the recent *Inflation Reduction Act* also provides tax credits for qualified used BEV purchases. Given its potential to support BEV adoption, understanding the resale market for BEVs is just as important for policymakers as it is for auto industry economists. Yet, to-date, there has been little empirical analysis of this market and its unique characteristics and defining features in

[1] Authors' calculations based on data from Wards Intelligence datacenter.
[2] The share of BEVs among new light vehicle sales in the U.S. market stood at 7% in 2023 (through July) based on numbers from Wards Autobank.

comparison to the more widely studied used car market for ICE vehicles (see Porter and Sattler, 1999).

Here, we provide for the first time a general description of the market for used BEVs. Utilizing comprehensive vehicle registration records for all new and used vehicle from model years 2010-2022 (with registration dates spanning January 2009 to December 2022), we distinguish among four mutually exclusive powertrain categories: vehicles powered by internal combustion engines, hybrid vehicles including plug-in hybrid vehicles (PHEVs), vehicles with a mix of powertrain options, and pure battery electric vehicles. We define a product as a model year of a specific vehicle make and model and its age as the difference between the year of its registration and its model year and introduce a novel measure of the market's depth that approximates the percentage of new vehicles in our panel that have been sold to the resale market. We refer to this measure as the used prevalence ratio (UPR).

Using the UPR and vehicle characteristics derived from our panel, we document two stylized facts: (1) BEVs are absorbed into the resale market at the slowest rate compared to all other powertrain types, and (2) BEVs exhibit significantly lower vehicle miles traveled (VMT) than other vehicles. We then connect these features of the resale market, employing Pseudo Poisson Maximum Likelihood (PPML) estimators to model counts of used vehicle registrations across all powertrain technologies. Our results uncover significant behavioral differences between BEV and ICE vehicle owners in how utilization (both on average and at the margin) leads to these vehicles being resold. By way of a counterfactual exercise that equalizes average VMT, we show that these differences can explain from 10-30 percent of the differential rates of transition from new to used vehicle status we observe between BEVs and ICE vehicles in our data.

We contribute to a broad literature on resale markets for durable goods (Schiraldi, 2011; Busse et al, 2012; Jacobsen & van Benthem, 2015; Gillingham et al, 2022), in addition to active areas of research on the economics of BEVs. Several surveys from California suggest that BEVs are driven just as intensely as vehicles with other powertrains (Hardman et al, 2018), while others have, *like us*, found BEVs to be driven significantly less so, e.g., as little as half as many miles per year as gasoline vehicles (Davis, 2019; Burlig et al, 2021; Muehlegger & Rapson, 2021). Our work also builds upon a growing literature on the demand for EVs that has examined, among other things, the role of public charging infrastructure (Sinyashin 2021, Springel 2021), home charging availability (Davis 2022), and financial incentives on EV adoption (Muehlegger & Rapson, 2018; Armitage & Pinter, 2022). This paper, however, is most analogous in spirit to Gillingham et al (2023), who examine attributes of EVs with respect to *new* sales in the U.S. between 2014 and 2020 using similar microdata on vehicle registrations.

The remainder of the paper proceeds as follows: In Section 2, we describe the vehicle registration database. In Section 3, we describe our approach to modeling the used vehicle market, introducing the used prevalence ratio. Section 4 presents our empirical analysis and includes our counterfactual exercises. We then conclude with policy implications in Section 5.

2. Creating a Dataset of U.S. Vehicle Registrations

Below, we describe the panel of new and used vehicle registrations from which our analysis of the depth of the resale market for battery electric vehicles is derived.

a. Data Sources, Restrictions, and Matching

We utilize data from two sources: Experian Automotive's Autocount database and the Wards Intelligence data center. Experian Automotive's Autocount data includes microdata on the universe of non-fleet vehicle registrations in the U.S., sourced from DMV title and registration data. From Autocount, we obtain data on the make (e.g., Chevrolet), model (e.g., Blazer), model year, odometer reading, registration date (month-year), new or used indicator, lease indicator, and owner zip code of all vehicle registrations from MY2010 to MY2022. The resulting dataset comprises observations with registration dates that range from January 2009 to December 2022. We begin the sample with model year 2010 to anchor the analysis to the beginning of BEV sales in the U.S.[3] Wards Intelligence provides data on total sales of new vehicles by make, model, model year, powertrain, and segment. We match Wards Intelligence data with the Autocount registration data to attach information on a model's powertrain (e.g., gasoline, electric, hybrid, etc.) and segment group (e.g., large Cross-over Utility Vehicle, or CUV) to the registration data.

[3] The first U.S.-produced BEV of the modern era was GM's EV1. It was produced from 1996 to 1999 and made available via lease in only a very small region of the U.S. market. It is therefore not included in the analysis of this paper. Mass-produced BEVs came to market in the late 2000s with the 2008 Tesla Roadster and the 2010 Nissan Leaf. We start our analysis with MY 2010, which includes the first sales of the Nissan Leaf. For reference, while the Tesla Roadster started selling in 2008, less than 1,400 units were sold of that model by the time production stopped in 2011.

After obtaining all MY2010 to MY2022 vehicle registrations from Autocount, we start with 289,480,798 registrations. We then match those with the Wards Intelligence data on make-model-model year. The match rate between Autocount and Wards Intelligence is approximately 96%, with the majority of registrations representing ICE vehicles. The match rate split out by powertrain bucket is reported in Table 1. The four mutually exclusive powertrain buckets are defined in the next section.

b. Panel Creation

The registration data provided by Autocount does not come with VIN numbers. As a result, we cannot track a unique vehicle from owner to owner. To circumnavigate this limitation, we collapse our data of 278,979,072 matched registrations into a panel such that an observation is a product-age. A product is defined as a vehicle make-model-model year, and age is defined as the difference between year (of registration) t and model year v. Note that it is possible for age to be negative as “new car” model years are not necessarily in sync with calendar years. Manufacturers often introduce new model year vehicles in the calendar year prior. As an example, a MY2023 vehicle could be sold and registered in March 2022. Note that since this analysis is interested in looking at used vehicle registrations, negative ages will be quite rare: few consumers will purchase a brand-new vehicle and immediately turn it over to resale.

While the registration data is offered at a monthly frequency, we aggregate to an annual frequency due to potential lags in the registration data. In particular, used vehicles are not necessarily registered in the month when they are purchased as most states give purchasers a few months before registration is required. We also aggregate the data to the national level, assuming that the market for used vehicles is nationally integrated. We calculate several properties for each product at a given age: the total number of new registrations, total number of used registrations, and the mean moment of the odometer readings[4] for both new and used registrations we also know the segment and powertrain product which are fixed for a product across time.

[4] Note that the only data cleaning we perform prior to collapsing the matched registrations into a panel relates to the odometer readings of the 278,979,072 matched registrations. Some (new and used) registrations had unrealistically high odometer readings (999,999 miles for example). To address these outlier issues, we set all odometer readings greater than the 99.9th percentile to missing for both new and used registrations.

For our analysis we define four mutually exclusive powertrain buckets to which we assign each product. The ICE bucket is comprised of products that run on gasoline, diesel, or natural gas. The BEV bucket is made up of products that run exclusively on electricity. The hybrid bucket contains products that are classified as either conventional hybrids or plug-in hybrids. Finally, the mixed bucket contains products that contain a mix of power types (i.e., the 2012 Ford Escape offered both gasoline and hybrid versions). Table 2 summarizes the registration and product-age share of our dataset by bucket. The ICE and mixed buckets dominate across (new and used) registrations and product-age observations. Using new sales data from Wards Intelligence, we find that most vehicles in the mixed bucket feature internal combustion engines. We are confident that the share of BEVs that originate in the mixed powertrain bucket is trivial. See Appendix B for a more detailed analysis of the composition of the mixed powertrain bucket by sales volume.

Products are also assigned to a "segment", a type of automotive classification used by Wards Intelligence that categorizes vehicles according to size, purpose, and performance. In total, there are 27 segments. An example of a segment is a "small Crossover Utility Vehicle (CUV)". Segments are nearly always fixed for a model year. Occasionally a carmaker implements a mid-model-year changeover to a different segment for a specific product. For instance, the 2021 Hyundai Tucson covers both segments Small CUV, (S17), and Middle CUV, (S18). Because we cannot distinguish these segments once we aggregate to the product level, we set products with multiple segments in a model year to missing. Note that this is a rare occurrence (less than 1% of all new and used registrations combined). To find a tabulation of registrations by segments, refer to Table 3.

c. Heterogeneity of Used Registration Counts

To get a sense of the used registration counts in our panel framework, and the heterogeneity that exists for this measure across several dimensions, we start the analysis with Figure 1. Figure 1 reports two statistics for used registrations by powertrain bucket, across age: (1) the total used registration counts, pooled across all products, in Panel A and the (2) mean used registration counts, by product, in Panel B. Focusing on Panel A, we first see that ICE dominates across all ages in terms of total pooled used registrations. At age 3, there are over twice as many used ICE registrations as there are mixed registrations, and multiples more of both ICE and mixed used registrations than of the other two powertrain buckets. Another important feature is that each of the lines follows the same pattern: between ages 0 and 3 the pooled used registrations are strictly increasing across all powertrain buckets, with the max reached at age 3. Starting at the age of 4, the pooled used registration counts strictly decrease. Given the sum of used registrations by powertrain bucket reported in column 2 of Table 2, it is not surprising that ICE dominates on this dimension across all ages.

Note that the pattern of the lines in Figure 1 Panel A is a feature of the data that is due to both market dynamics and data structure. Regarding market dynamics, products of age 2-4 are often quoted as the "sweet spot" for buying used vehicles given that late model used cars tend to have lower mileage and retain some of their "new vehicle" qualities. The structure of our data shapes Figure 1 in the following way: we are only looking at products representing MY2010-MY2022, registered from calendar years 2009-2022. As the MY of a given product increases, the maximum age it can achieve within our data decreases. Hence, the number of unique products at each age decreases with age.

Panel B of Figure 1 reports the mean used registration counts across all products by age and powertrain bucket. Compared to Panel A, Panel B shows that mixed products have, on average, more used registrations than any other powertrain bucket. As a matter of fact, the mean used registrations for mixed products at age 3 is over twice the size of the same measure for ICE products at age 3. Why the discrepancy between Panel A and Panel B? The reason is that mixed products represent high volume vehicles. From an economic perspective, manufacturers want to pair multiple powertrain options to vehicles they are confident will sell many units. That explains why we see such high-volume products in the mixed category including models such as the 2018 Toyota RAV4 and the 2012 Honda Civic.

Of course, heterogeneity exists along several other dimensions as can be observed by looking at the mean used registration counts of the products in our dataset by age. Figure 2 reports mean registration counts for three other dimensions relevant to our analysis: by year of registration, vehicle segment, and vehicle make. Note that Panel A consists of all years of registrations in our dataset, but Panel B and C only include 4 segments and makes, respectively, to make the graphs readable. The key takeaway from these figures is that the heterogeneity in used registration counts must be taken into account in our formal analysis if we want to isolate the impact of powertrain on the used vehicle market. To see the pooled used registration counts across these three dimensions, refer to Appendix A, Figure A1.

d. Vehicle Miles Traveled

There is active debate amongst researchers as to whether BEVs are driven as much as vehicles of other powertrains. The reason is that vehicle miles traveled are difficult to measure directly. This paper contributes to this active debate by utilizing the odometer reading information we observe for each registration in the Autocount dataset. We suggest this as a good indicator of vehicle usage as it is an administrative measure of the odometer reading of each vehicle at the time of its registration, each time it is registered. We proxy vehicle usage in our panel framework with the mean odometer reading of all used registrations of each product-age observation in our dataset. We refer to this measure as vehicle miles traveled (VMT). Note that we do not observe the odometer readings of vehicles that never change hands after initial sale to the first owner. Given the fact that resale decision and mileage likely correlate, we conduct a lower bound estimate of our VMT measure in Appendix C.

Figure 3 plots the average VMT of all products in the dataset by age and powertrain bucket. One fact that immediately jumps out is that the average VMT for BEVs is significantly lower across all vehicle ages. Furthermore, BEVs are found to be the only outlier in this exercise as the average VMT for ICE, hybrid, and mixed registrations map remarkably close to one another, suggesting usage across these three powertrain categories does not vary materially at the national level. To see the average VMT for each powertrain bucket weighted by used registrations, refer to Appendix A.

One somewhat odd feature of the data that exists across all four powertrains is that the mean VMT decreases after age 9. The reason for this is like the patterns we observed in used registration counts: there are relatively few unique products that make it to these older ages in our dataset. With such few unique products at older ages, we don't observe many used registrations. That is evident in Figure 1. With fewer used registrations in the right tail of age, we observe comparatively fewer odometer readings to calculate our VMT measure. We find this feature of the data to be consistent across all products.

The rest of this paper will focus on further exploring the used BEV market, exploiting the variation in VMT across powertrain buckets to identify how it impacts the transition to the used vehicle state for BEVs. In the next section, we introduce a novel measure for the depth of the auto resale market, the used prevalence ratio. We then introduce more formal econometric methods to the analysis.

3. Measuring Used Vehicle Market Depth: The Used Prevalence Ratio

To measure the depth of the used vehicle market we adapt a measure from the epidemiology literature. *Point prevalence* in epidemiology refers to the proportion of a population that exhibits a given characteristic at a specific point in time. We measure the depth of the used vehicle market in a similar manner. For a given category (where a category can be a product, powertrain type, or even the whole market), this involves calculating two objects: 1) the cumulative number of used registrations of category c at age a, and 2) the total number of new registrations of that category across our entire sample period.

We refer to this novel measure of market depth as the used prevalence ratio (UPR), defined as

$$(1)\ UPR_{c,a} = \left(\frac{\sum_a ur_{c,a}}{tnr_c} \middle| a = t - v\right)$$

where $\sum_a ur_{c,a}$ is the cumulative number of used registrations of category c at age a (defined as year of registration, t, less model year, v), and tnr_c is the total number of new registrations ever in our sample for category c. The UPR is approximately equivalent to the percentage of new vehicles in a category for a given age that have transitioned to the used vehicle market. The numerator is constructed directly from the used registration counts discussed in Section 2b and 2c, and the denominator allows us to represent the whole of the new market for a category.

Defining used vehicle markets in these ratio terms allows us to directly compare them regardless of volume, something that we would not be able to do when strictly comparing used registration counts. Note, however, that our definition allows for the possibility that the UPR surpasses 1. This is because we cannot restrict the sample to only include the first sale of a vehicle into the used market as Autocount does not include any information regarding a vehicle's VIN. As a result, the same vehicle can be registered as used more than once in our sample. In other words, we cannot track whether a given used registration indicates the first time a vehicle changes owners from a new registration to a used registration, or if it transitions from one used registration to another.

Figure 4 demonstrates the flexibility that the UPR measure offers given our data constraints. Panel A plots the UPR for the entire market (i.e., all products). It provides an approximate estimate of the percentage of all new vehicles in our dataset that have been sold to the used market. Early in the market's lifecycle, particularly between ages 0 to 3, the UPR grows rapidly (consistent with figure 1). As the products get older, this ratio levels off after age 3, approaching a value slightly below 1. This slowdown in the resale market for older vehicles can be due to several reasons, including declining interest in older vehicles and vehicles exiting the dataset, for example through scrappage or exportation. Note, however, that we cannot directly observe if a vehicle exits the dataset, since we do not have access to vehicle identifiers.

Panel B of Figure 4 plots the UPR by powertrain technology and illustrates the primary motivation for this paper: the finding that the UPR of BEVs is substantially lower than that for either the ICE, mixed, or hybrid products. By age 12, approximately only 20% of BEVs have been sold to the used market, while the ratio at the same age is approximately 63% for hybrids, 82% for mixed, and 90% for ICE. Clearly, there are structural factors holding back the resale market for BEVs. While we do not attempt to capture these factors in a structural model, we do analyze them below in a reduced form statistical model that we can use to better quantify the behavioral differences that exist in the resale market for BEV and other vehicle owners.

Underlying the UPR measure is count data. The UPR is constructed by simply translating this count data into a ratio. In the next section, we will introduce Pseudo Poisson Maximum Likelihood Models (PPML) to estimate the used registration counts of all the product-age observations in our panel. From here, we can use the model coefficients to generate predicted used registration counts for all observations in the analysis sample. Utilizing these predicted used registration counts, we can next construct a predicted UPR by powertrain type to see how well our statistical models fit the real data. Finally, we conduct a counterfactual exercise to see how the UPR would be impacted if BEVs were driven just as much as ICE vehicles. This will allow us to estimate the extent to which differences in vehicle usage drive the gap in Figure 4, panel B.

4. Empirical Analysis: Modeling Used Vehicle Counts & Counterfactuals

Next, we describe the statistical models used to capture the empirical regularities of the UPR and conduct counterfactual inference based on differences in usage across BEVs and ICE vehicles.

a. Baseline to Preferred Specification

We begin by modelling the relationship between powertrain technology and used vehicle registration counts for all product-age observations in our dataset. Specifically, we propose the following baseline specification to model used registration counts, y, for product p at age a:

$$(2)\ y_{p,a} = \exp[\beta powertrain_p + \vartheta_{m(p)\times a} + \varphi_{s(p)\times a} + \gamma_{y(p)\times a}] \cdot \varepsilon_{p,a}$$

The functional form above is motivated by the fact that our outcome measure, used vehicle registrations, is a count variable. Previous literature has highlighted the importance of using Poisson regressions when analyzing count-variable outcomes (Cohn et al, 2022). The variable of interest, $powertrain_p$, is a categorical variable indicating if a given product is ICE, mixed, hybrid, or BEV. In the estimation of equation (2), we make ICE the base level for purposes of comparison.

We also include in equation (2) a number of two-way fixed effects to control for categorical and time-varying heterogeneity in used vehicle registration counts: $\vartheta_{m(p)\times a}$ are vehicle make (of product p) × age fixed effects, $\varphi_{s(p)\times a}$ are vehicle segment (of product p) × age fixed effects, and $\gamma_{y(p)\times a}$ are year of registration × age fixed effects.[5] These fixed effects ensure that our relationship of interest, β, is not impacted by vehicle make, vehicle segment, and the year in which the vehicle was registered over all ages in our sample. We estimate the fixed effects Poisson regression implied by equation (2) with the Pseudo Poisson Maximum Likelihood (PPML) procedure of Correia et al (2020) with heteroskedastic robust standard errors.

Our preferred model specification deviates slightly from above as summarized by the equation:

$$(3)\ y_{p,a} = \exp[\beta powertrain_p \times (1 + \alpha VMT_{p,a} + \varphi total\ new_p) + \vartheta_{m(p)\times a} + \varphi_{s(p)\times a} + \gamma_{y(p)\times a}] \cdot \varepsilon_{p,a}$$

[5] Note that we cannot include model year-age fixed effects because we already include age and year fixed effects. Two of the three time-dimensions (model year, age, and year of registration) determine the last.

The difference between equation (2) and equation (3) is that we include two interactions in the latter: (i) the vehicle miles traveled measure of product p at age a, $VMT_{p,a}$, interacted with $powertrain_p$, and (ii) the total number of new registrations in our sample for product p, $total\ new_p$, interacted with $powertrain_p$. Controlling for VMT and the total number of new registrations ever are important as we expect both variables to positively correlate with used vehicle registration counts. The more usage a product gets, the higher the likelihood is it will get sold in the resale market. Likewise, the higher volume a product represents, the more likely it will have higher used registration counts. These effects, however, cannot be appropriately identified if they are assumed to be constant across powertrain types. As such, we interact these two variables with powertrain due to their likely differential effects and estimate equation (3) with the PPML procedure and heteroskedastic robust standard errors.

Column 1 of Table 4a reports the baseline specification of our model. All relevant coefficients on the powertrain types are statistically significant at the $p < 0.01$ level. Products assigned to the BEV category are expected to have -1.622 less used registrations in log counts than ICE products at a given age, controlling for make, segment, and registration year. Products assigned to the hybrid powertrain type also have fewer used registrations in log counts than ICE products, an estimated 1.220 fewer. Finally, products assigned to the mixed powertrain type are expected to have about 0.338 more used registrations in log counts than ICE products.

In column 5 of Table 4a we report the coefficients of our preferred specification. The coefficients on the powertrain types all remain statistically significant at the $p < 0.01$ level in this specification and have approximately the same magnitude as before. Similarly, all the coefficients on VMT are significant at the $p < 0.01$ level in this specification, but the coefficient for BEVs is much larger than the other powertrain types. All else equal, an additional VMT of 10,000 miles for a BEV product is expected to produce 0.505 more used registrations on average whereas for an ICE product it is 0.184 more used registrations on average, both in log counts.[6]

[6] Note that the difference in the slopes for the powertrain and VMT interactions are all significantly different from one another. We report Wald test results that show this in Table 4b.

This difference is significant for understanding the depth of the BEV market relative to other powertrain types. It indicates, for instance, that as VMT increases, there is a higher marginal propensity for a BEV product to be sold to the used market than for a product in any of the other powertrain categories. Furthermore, at high enough levels of VMT, this effect even becomes large enough to offset and potentially counteract whatever are the behavioral reasons for why BEVs on average transition less frequently to the resale market than any other powertrain type.

We find similar differential effects across powertrains when looking at the interactions between powertrain and total new registrations as well. Conditional on an additional 10,000 total new registrations of a product, BEVs are expected to have 0.127 additional used registrations whereas ICE products are expected to have 0.067 more used registrations, both in log counts.[7] The remainder of Table 4a decomposes the differences between our baseline and preferred model specifications. In these models, we allow one or both of VMT and total new registrations to explain the used registration counts of all powertrain types equally without making allowance for the marginal differences across powertrains in our preferred specification.

b. Model Fit to Used Prevalence Ratio

With the estimated coefficients from Table 4a, we can reconstruct the UPR measure by powertrain type based on our models. To do this, we use the model coefficients to predict the used registration counts for each product-age observation in the analysis sample. From here, we reconstruct the UPR for each powertrain technology to see how well our statistical models can approximate the behavior of the real data. For this exercise, we focus on the models in column 2 and column 5 of Table 4a, henceforth named model 2 and model 5. Model 1 in that table is considered as our baseline specification. Model 2 treats both VMT and total new registrations uniformly across powertrain types. Model 5 is our preferred estimation strategy from equation (3). Given the importance of the differential effects that we find across powertrain technologies for both of these two variables, we suggest that this is the best comparison to discuss.

[7] Most of the differences between powertrain types are statistically different from one another here as well, as confirmed by the Wald tests shown in Table 4b.

Panel A and B of Figure 5 display the fits of model 2 and model 5, respectively, to the real UPR data by powertrain type. Note that these predictions include both the linear predictions and the 95% confidence interval bands. Comparing the model fits, both models fit the ICE and mixed UPR almost perfectly. Given the large number of registrations within each of these types, this is not surprising. The key difference in the fit of the models comes into view when comparing the hybrid and BEV predictions. Model 2 overestimates the UPR for both the hybrid and BEV powertrains. On the other hand, the differential slopes in VMT and total new registrations allowed for in Model 5 calibrate to the data markedly better. To see how well models 1, 3, and 4 from Table 4a fit the real UPR data, refer to the appendix Figure A3. It turns out that all of our models do a rather good job of fitting the real data; however, Model 5 is our preferred choice.

c. Counterfactual

Having shown that our statistical models fit the UPR by powertrain data rather well, we next construct a counterfactual exercise in which we allow BEV products to be driven at the same level on average as ICE products. To do this, we first impute the average VMT by age for ICE products to all BEV product-age observations in our analysis sample. This ensures that the ICE and BEV lines from Figure 3 are perfectly aligned. We then utilize the coefficients from the models in Table 4a to predict a counterfactual UPR for the BEV products. This exercise allows us to see what the UPR would look like if BEVs were utilized at the same rate as ICE vehicles.

Note, however, that this counterfactual exercise represents a rather extreme shock to the VMT for BEV products in our dataset, as it *equilibrates* ICE and BEV usage. It is possible that a counterfactual of this scale could in fact also influence the coefficients that we report in Table 4a. We keep that in mind when we interpret the results of our counterfactual exercise below, essentially interpreting them as potential upper and lower bounds on the behavioral responses that are likely to result from such a shift in utilization patterns by BEV owners.

Figure 6 reports the results of this counterfactual exercise when using the coefficients for Model 2 and for Model 5. Panels A and C report the UPR over age by powertrain bucket for Models 2 and 5, respectively. Panels B and D report for each age the percentage difference in UPR between the BEV and ICE line explained by VMT. This is calculated by subtracting the actual BEV UPR from the counterfactual BEV UPR and dividing this difference by the ICE UPR.

Panel A shows that, assuming that the impact of VMT on the UPR is uniform across powertrains as specified in Model 2, there is a slight increase in the counterfactual UPR for BEVs. At age 1, VMT explains around 13% of the difference in UPR between the BEV and ICE used vehicle markets. By age 10, this percentage settles to approximately 10%. Moving to the counterfactual exercise for Model 5 in Panel C, however, we see how important it is to allow for differences in utilization both on average and on the margin across the four powertrain types . At age 1, VMT accounts for approximately 9% of the difference in UPR between the BEV and ICE line. By age 10 we see a marked increase:34% of the difference can be explained by VMT.

Comparing these different counterfactual results yields some significant insights. In both counterfactuals, we assume that BEVs are driven at the same rate as ICE vehicles. But in model 2 we require the effect of extra mileage on the UPR to be identical across all powertrain types, whereas in model 5 we allow additional mileage to lead BEVs to transition more quickly into the used vehicle market, per our coefficients in Table 4a. The counterfactual result from model 5 suggests that strong behavioral reasons exist for the differences we observe in how VMT affects transitions into the used market between ICE and BEV products, as they can explain up to 1/3 of the difference in the UPR. This represents an economically significant magnitude worthy of future study as to the underlying structural factors driving these owner differences.

The keys to this finding are the differential effects in how VMT leads transitions into the used market across the powertrain types, reflected in the differential coefficients in Table 4a that allow us to preserve the unique features of BEV owner behavior in our counterfactual. We believe that the dramatic increase in UPR in the model 5 counterfactual provides an upper bound for the behavioral response to the BEV usage shock that we impute. It is likely that such a shock would, itself, cause BEV owners to behave in a manner more consistent with ICE owners and therefore alter the parameters of model 5 to perhaps look more like model 2. Even with this stipulation, however, the counterfactual UPR estimates derived from model 2's parameters still explain about 10% of the difference in UPR between ICE and BEV products.

5. Summary

Our results demonstrate the importance in understanding the drivers of utilization differences across BEV and other vehicle type owners for the broader adoption of this new propulsion technology. We arrived at this conclusion by establishing the stylized facts of much lower utilization and rates of transition to the used vehicle market for BEVs compared to vehicles featuring all other powertrain technologies. In utilizing statistical models designed to explain used registration counts, we discovered that behavioral reasons driving differences in the utilization rate of BEVs significantly contribute to the rate at which these vehicles are resold. Through counterfactual exercises equilibrating BEV and ICE levels of utilization, we then estimated that differences in their utilization patterns can explain between 10% and 34% of the difference in the depth of the used vehicle market for BEVs relative to ICE vehicles.

Given these findings, there are important policy implications to consider. The resale market represents an important transmission mechanism for BEV technology to the car-buying public. Given the policy push for wider adoption of BEVs, our findings highlight the importance of BEV usage. Public investment in charging infrastructure could support an increase in BEV VMTs, which our findings suggest would improve activity in the resale market. Potential network effects of this kind exploit the historical link between public infrastructure and productivity in the U.S. for autos. Fernald (1999), for instance, highlights how the development of the interstate highway system disproportionately affected productivity growth in U.S. industries with more vehicles.

Observations from markets outside of the U.S. illustrate how public investments in charging infrastructure allow for BEVs to thrive. In Norway, for example, electric vehicles accounted for 79% of new passenger vehicles sold in 2022. Like the U.S., Norway offers several tax incentives that make purchasing electric vehicles more financially attractive. However, the Norwegian government has also heavily invested in electric vehicle infrastructure: subsidies are offered to housing associations that purchase and install electric charging stations and the government has committed to establishing municipal fast charging stations every 50 km (Clynes, 2022). Our results suggest that such investments in the U.S. may be necessary to support the broader utilization and adoption of BEVs.

While usage is important in explaining why new BEVs are absorbed into the resale market at a much slower rate than ICE vehicles, our results suggest that around two-thirds of the difference in absorption rates is beyond the scope of factors driving usage differences alone. In that regard, it is worth mentioning that our upper bound estimate suggests that the positive shock to VMT would make BEV absorption into the resale market resemble that of hybrid vehicles. Hybrids are also absorbed into the used market at a much slower rate than ICE or mixed vehicles, even though range anxiety is not an issue with that propulsion technology. This too suggests a possible role for certain characteristics of owners of vehicles featuring green technology, such as hybrids and BEVs, in explaining why they do not sell their new vehicles nearly as quickly as ICE vehicle owners (see for example Buhmann and Criado, 2033). This is a question that we leave for future research to address.

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7. Tables and Figures

Table 1. Match Rate between Wards Intelligence and Autocount Registration Data and shares of matched Data by Powertrain Bucket

Level	Observations	Matches (Match Rate)	ICE (Share)	Mixed (Share)	Hybrid (Share)	BEV (Share)
Registrations	289,480,798	278,979,072 (96.4%)	198,363,954 (71.1%)	75,162,809 (27.0%)	3,431,910 (1.2%)	2,020,409 (0.7%)

Note. The following table reports the match rate between data from Wards Intelligence data center and Experian's Autocount registration database. We wish to recover data on the powertrain technology and segment group of unique make-model-MY combinations from Wards. We match this information to the universe of nonfleet MY2010 to MY2022 vehicle registrations in Autocount. The Autocount database reports 289,480,798 registrations, and we match 96.4% of these registrations to the Wards data. Of the matched registrations, Columns (4) to (7) reports the number and share of registrations that make up each of four powertrain buckets.
Source: Wards Intelligence and Autocount

Table 2. Sum and Share of Product-Age Observations and the Registrations they Represent, by Powertrain Bucket

Bucket	New Registrations	Used Registrations	Product-Age	New Share %	Used Share %	Product-Age Share %
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	100	100	100

Note. The following table shows how our unit of observation (product-age) and the registrations these observations represent are distributed across the four powertrain buckets.
Source: Wards Intelligence and Autocount

Table 3. Number of Registrations and Product-Age Observations by Segment

Segment	New Registrations	Used Registrations	Product-Age
Missing	1,499,880	959,196	161
Lower Small Car	4,141,349	4,440,036	960
Upper Small Car	17,707,500	17,185,800	1,888
Small Specialty Car	930,648	951,030	857
Lower Middle Car	17,286,981	19,069,315	1,368
Upper Middle Car	2,426,343	2,527,287	880
Middle Specialty Car	2,065,463	2,612,521	505
Large Regular Car	1,600,153	3,574,742	561
Lower Luxury Car	5,725,830	5,804,438	1,844
Middle Luxury Car	1,781,909	2,111,408	1,311
Upper Luxury Car	747,216	643,262	1,054
Luxury Specialty Car	665,939	658,204	854
Luxury Sport Car	560,615	474,756	1,263
Small CUV	8,108,371	5,321,105	1,178
Middle CUV	29,452,490	21,323,500	2,226
Large CUV	4,769,386	3,517,553	608
Small Luxury CUV	911,176	716,051	352
Middle Luxury CUV	6,586,959	4,467,020	2,059
Large Luxury CUV	1,867,168	1,256,095	659
Small SUV	2,097,340	1,752,853	223
Middle SUV	5,325,913	4,547,989	585
Large SUV	2,448,302	2,792,715	737
Middle Luxury SUV	447,789	330,219	463
Large Luxury SUV	747,456	732,346	647
Small Van	4,120,895	4,409,547	905
Large Van	668,105	865,430	416
Small Pickup	4,567,398	2,684,262	564
Large Pickup	18,477,574	15,514,254	722
Total	147,736,148	131,242,934	25,850

Source: Wards Intelligence

Table 4. PPML Regression Analysis

Panel A: Coefficient Estimates of PPML Models, Used Registration Counts as Outcome

	(1)	(2)	(3)	(4)	(5)
BEV	-1.622***	-1.177***	-1.908***	-1.138***	-1.858***
	(0.082)	(0.082)	(0.134)	(0.083)	(0.132)
Hybrid	-1.220***	-0.625***	-1.136***	-1.144***	-1.301***
	(0.073)	(0.049)	(0.084)	(0.041)	(0.067)
Mixed	0.338***	0.164***	0.100***	0.406***	0.316***
	(0.020)	(0.014)	(0.027)	(0.017)	(0.026)
VMT (10,000s)		0.188***		0.184***	
		(0.018)		(0.018)	
Total New (10,000s)		0.063***	0.063***		
		(0.001)	(0.001)		
BEV x VMT			0.510***		0.505***
			(0.050)		(0.050)
Hybrid x VMT			0.296***		0.223***
			(0.020)		(0.020)
ICE x VMT			0.186***		0.184***
			(0.018)		(0.018)
Mixed x VMT			0.200***		0.205***
			(0.019)		(0.018)
BEV x Total New				0.131***	0.127***
				(0.023)	(0.022)
Hybrid x Total New				0.154***	0.150***
				(0.005)	(0.005)
ICE x Total New				0.067***	0.067***
				(0.001)	(0.001)
Mixed x Total New				0.053***	0.053***
				(0.001)	(0.001)
Constant	9.202***	7.548***	7.558***	7.525***	7.523***
	(0.010)	(0.086)	(0.086)	(0.085)	(0.085)
Observations	24901	24901	24901	24901	24901
Adjusted R Square	0.734	0.866	0.866	0.871	0.871

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

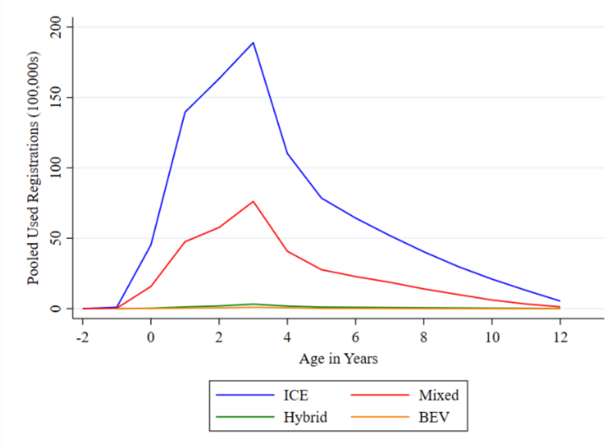
Panel B: Wald Test Results of Poisson Models' Coefficients, Prob. > Chi Square Reported

	Model (3)	Model (4)	Model (5)
Bucket x VMT All Equal	0.0000	-	0.0000
ICE x VMT = Mixed x VMT	0.0020	-	0.0000
BEV x VMT = Hybrid x VMT	0.0000	-	0.0000
Bucket x Total New All Equal	-	0.0000	0.0000
ICE x Total New = Mixed x Total New	-	0.0000	0.0000
BEV x Total New = Hybrid x Total New	-	0.3400	0.3054

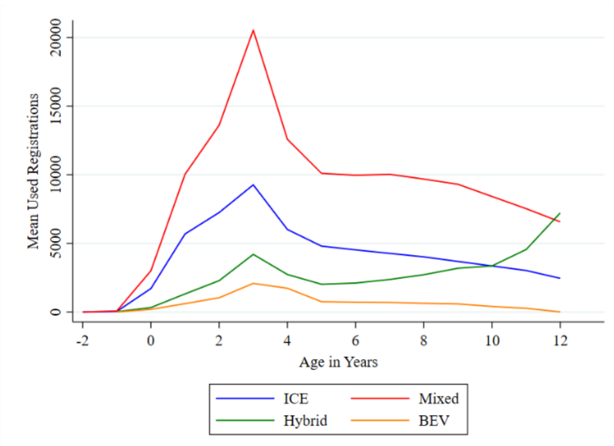
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure 1. Used Registrations by Powertrain Bucket

Panel A. Pooled Used Registration Counts over Age, by Powertrain Bucket



Panel B. Mean Used Registration Counts over Age, by Powertrain Bucket

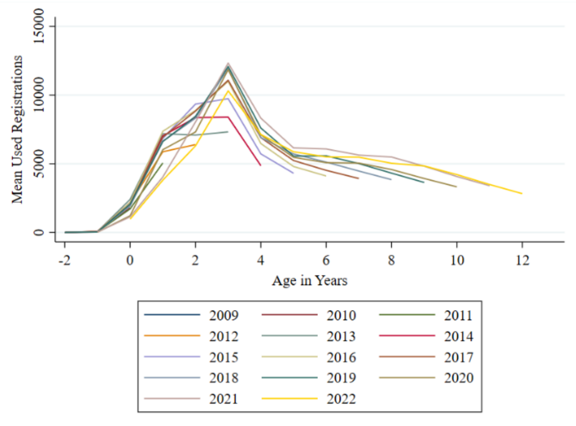


Note. Panel A takes the sum of used registrations by bucket across all ages in the panel. Panel B is the mean number of used registrations at the product level by bucket across all ages in the panel. On average, a mixed product has a higher number of used registrations than products in the other three powertrain buckets. In the aggregate sum, however, there are more ICE used registrations than mixed registrations. The reason for this is because mixed products are high volume vehicles, and there are also more ICE products than there are mixed products over all ages.

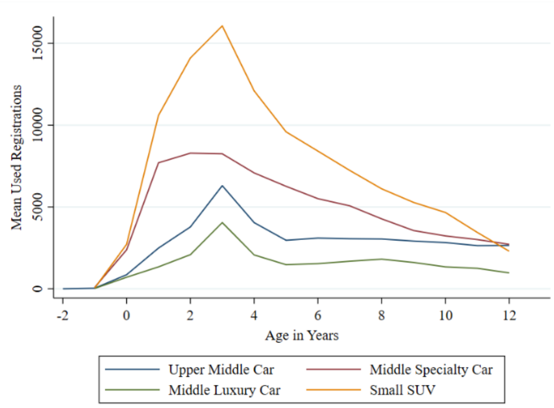
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure 2. Used Registration Count Heterogeneity

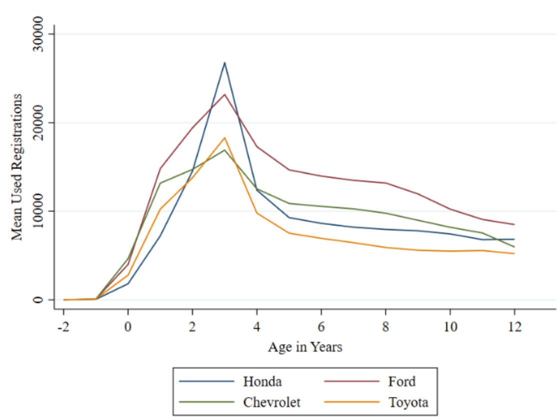
Panel A. Mean Used Registration Counts over Age, by Year of Registration



Panel B. Mean Used Registration Counts over Age, by Vehicle Segment



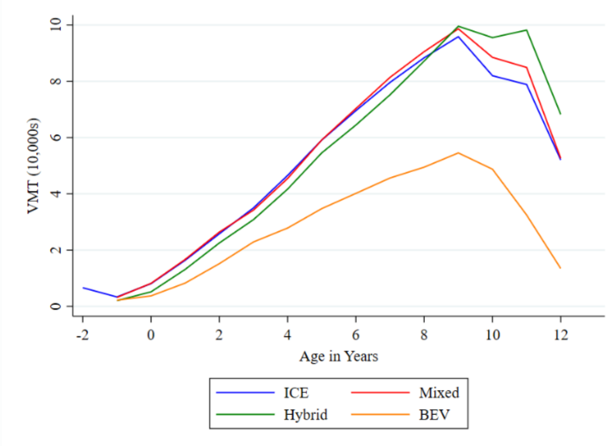
Panel C. Mean Used Registration Counts over Age, by Vehicle Make



Source: Authors' calculations based on data from Wards Intelligence and Autocount

Note. Each panel is the average number of used registrations at the product level by categorical group (year of registration, segment, or make) over age.

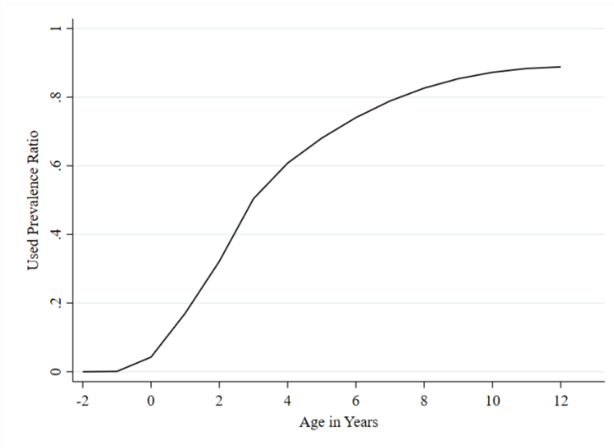
Figure 3. Mean Vehicle Miles Traveled over Age, by Powertrain Bucket



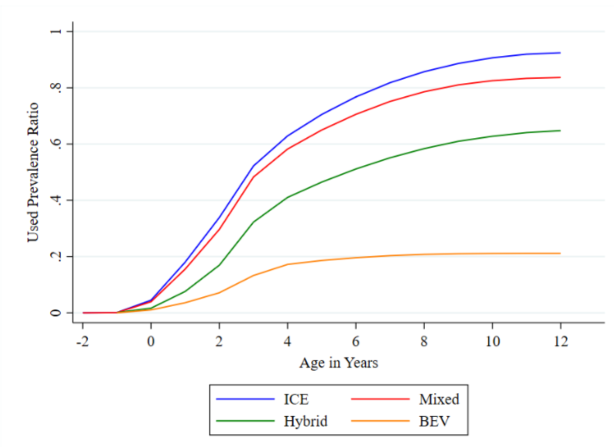
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure 4. Used Prevalence Ratio

Panel A. Used Prevalence Ratio over Age, Entire Market



Panel B. Used Prevalence Ratio over Age, by Powertrain Bucket

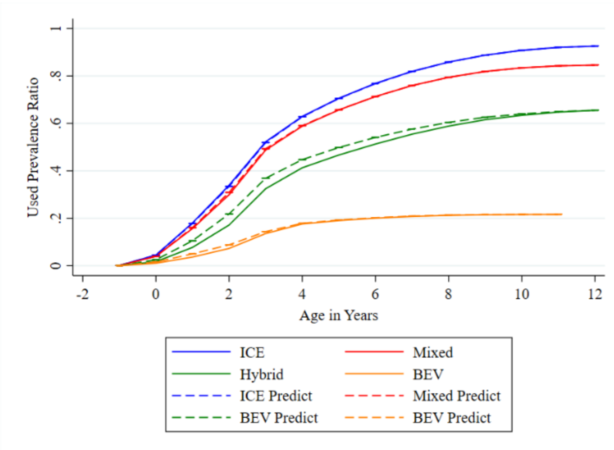


Note. Panel A is the pooled used prevalence ratio across all products in the dataset. We sum all used and new registrations by age and perform the calculation from Equation 1. Panel B performs the same calculation by summing all used and new registrations by age and powertrain bucket, and then performing the calculation from Equation 1.

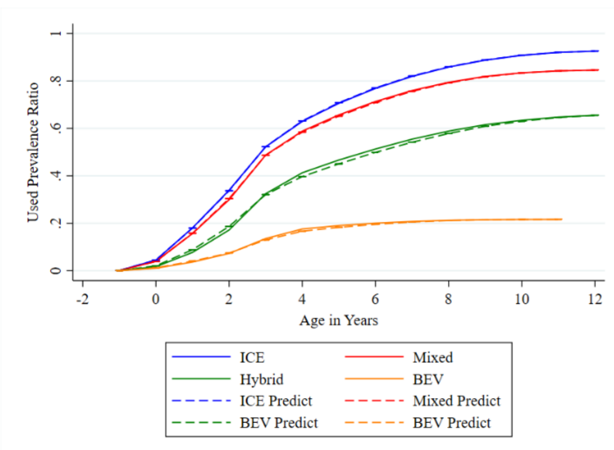
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure 5. PPML Fit to Used Prevalence Ratio over Age, by Powertrain Bucket

Panel A. Model 2 Fit



Panel B. Model 5 Fit

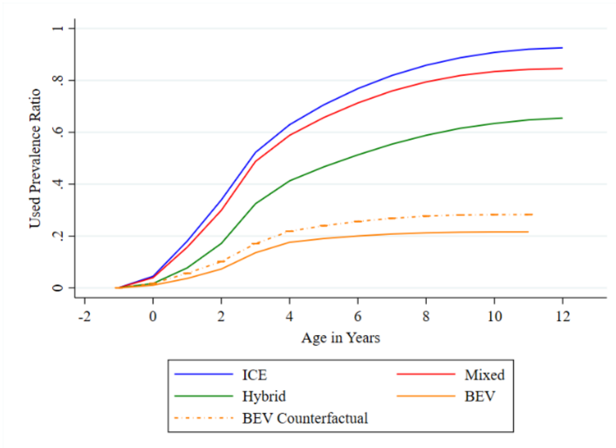


Note. The dashed lines of Panel A and B report the predicted used prevalence ratios by powertrain bucket, with standard error bars at the 95% Confidence Interval, utilizing the coefficients from Models 2 and 5, respectively (as reported in Table 4a). The solid lines of Panel A and B report the used prevalence ratios of the real data. All lines contain only the data from the analysis sample in the PPML estimates (n = 24901).

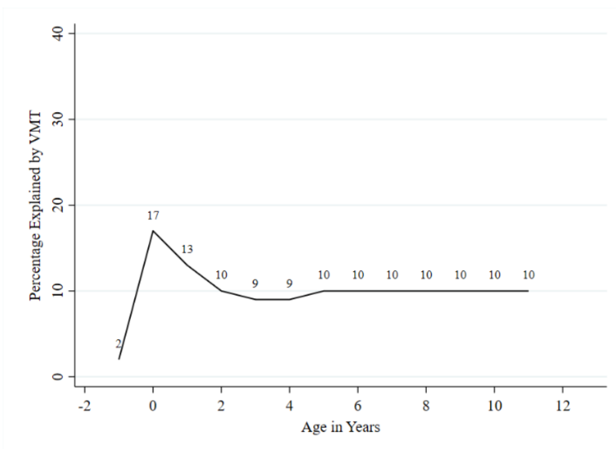
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure 6. Counterfactual Used Prevalence Ratio over Age, by Powertrain Bucket

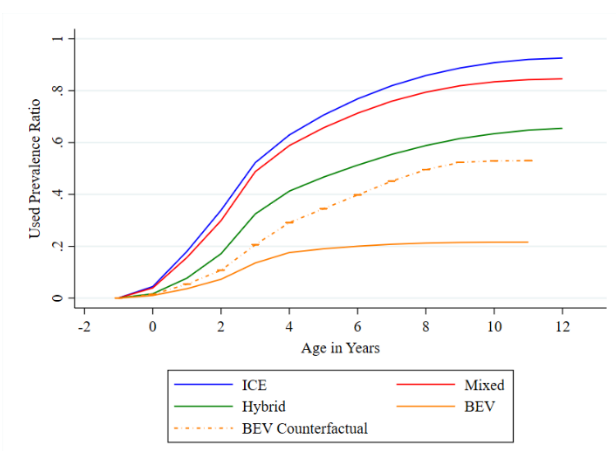
Panel A. Model 2 Counterfactual



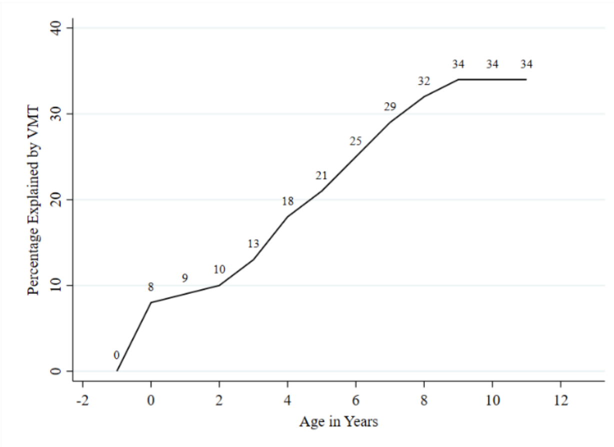
Panel B. Model 2 Percentage Explained by VMT



Panel C. Model 5 Counterfactual



Panel D. Model 5 Percentage Explained by VMT



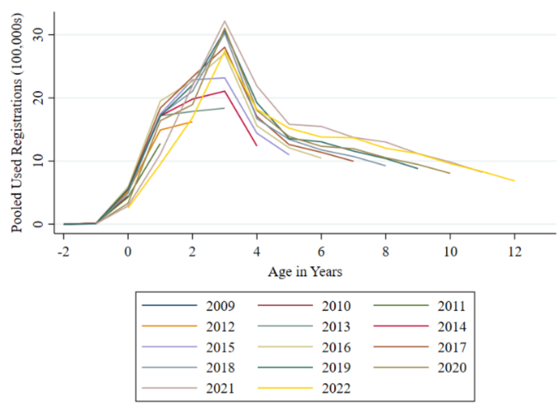
Note. Panel A and C report the real UPR by powertrain bucket measure for all four powertrain buckets. The counterfactual BEV line is constructed by imputing the average ICE VMT to all BEV product-age observations, predicting the number of used registrations utilizing this counterfactual age and the coefficients in the models from Table 4a, and reconstructing the UPR measure. The BEV counterfactual contains both the point estimates as well as the 95% confidence interval bands. Panel B and D report the percentage of the difference between the BEV and ICE UPR line explained by VMT. It is calculated by subtracting the actual BEV UPR from the counterfactual BEV UPR and dividing this difference by the ICE UPR.

Source: Authors' calculations based on data from Wards Intelligence and Autocount

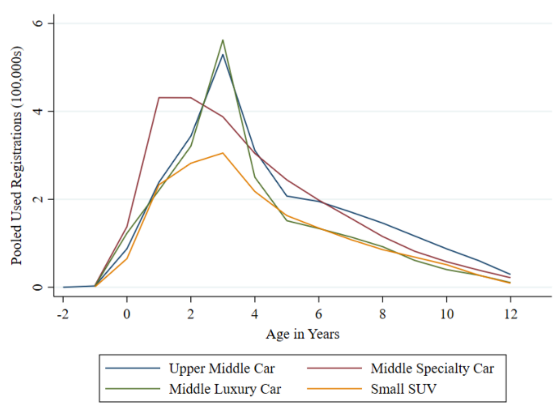
Appendix A.

Figure A1. Pooled Used Registration Count Heterogeneity

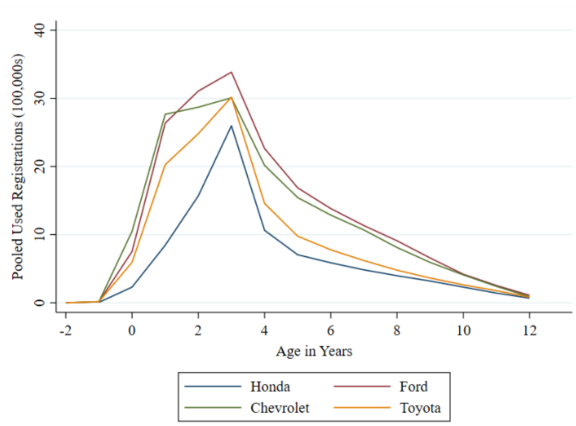
Panel A. Pooled Used Registrations over Age, by Year of Registration



Panel B. Pooled Used Registrations over Age, by Vehicle Segment

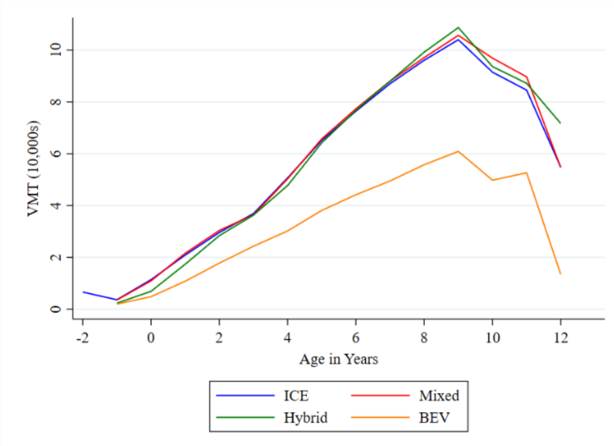


Panel C. Pooled Used Registrations over Age, by Vehicle Make



Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure A2. Mean VMT Weighted by Used Registrations over Age, by Powertrain Bucket

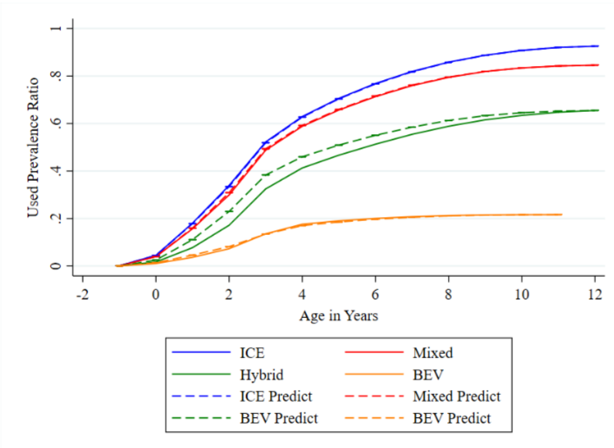


Note. This figure takes the sum of the odometer readings of all used registrations by age and powertrain bucket, and divides this sum by the total number of used registrations at a given age for a given bucket.

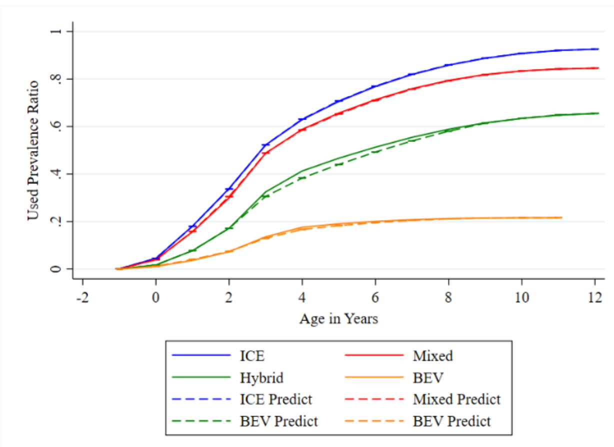
Source: Authors’ calculations based on data from Wards Intelligence and Autocount

Figure A3. PPML Fit to Used Prevalence Ratio over Age, by Powertrain Bucket

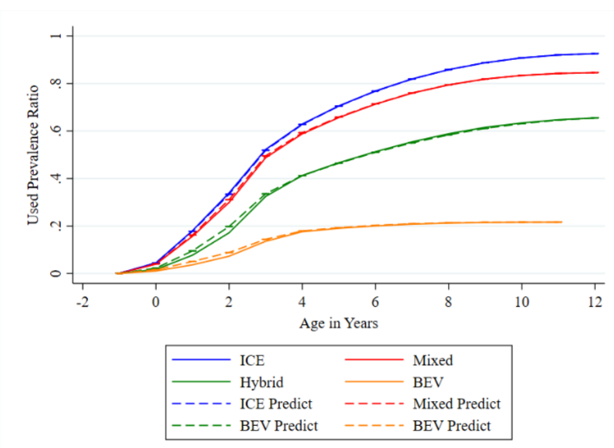
Panel A. Model 1 Fit



Panel B. Model 3 Fit



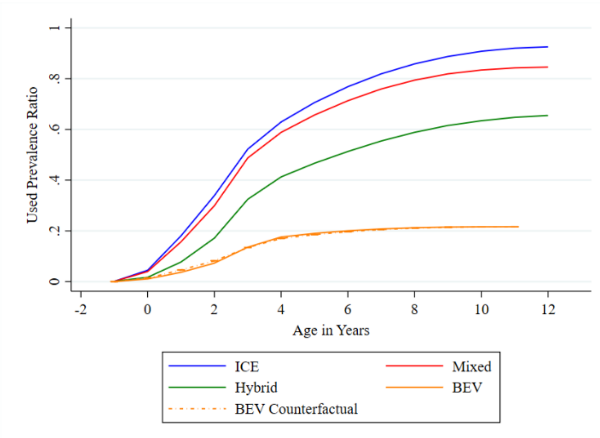
Panel C. Model 4 Fit



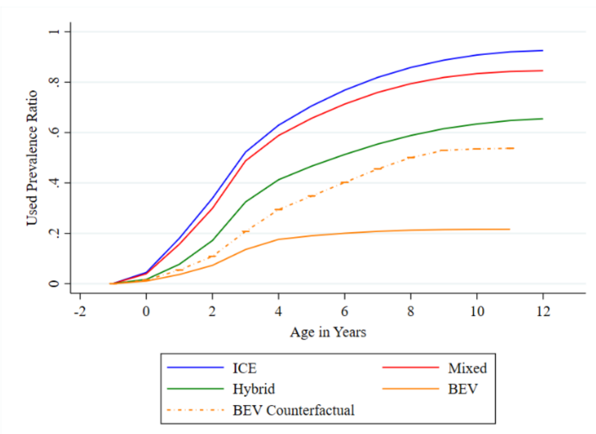
Source: Authors' calculations based on data from Wards Intelligence and Autocount

Figure A4. Counterfactual Used Prevalence Ratio over Age, by Powertrain Bucket

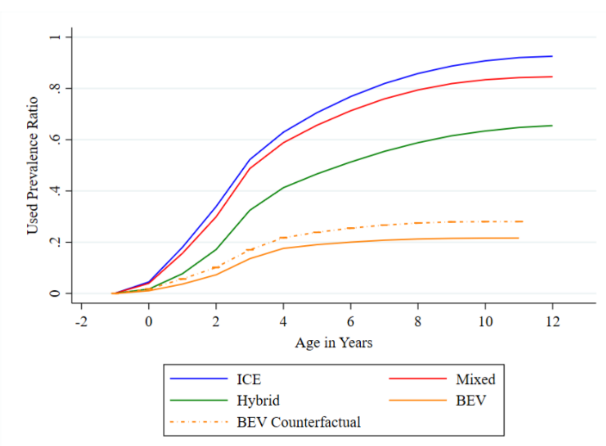
Panel A. Model 1 Counterfactual



Panel B. Model 3 Counterfactual



Panel C. Model 4 Counterfactual



Source: Authors' calculations based on data from Wards Intelligence and Autocount

Appendix B. Analyzing the Mixed Bucket

Given the fact that the mixed powertrain bucket is the second largest bucket by both unit of observations and number of registrations in our dataset, it is worth decomposing its contents. Table B1 reports the share of sales within the mixed powertrain buckets that are assigned to particular powertrain technologies. This table shows that most units within the mixed powertrain bucket are ICE vehicles. Furthermore, moving from left to right in the table, ICE vehicle share is declining as hybrids and BEVs become more popular options in more recent model years. Given the fact that the mixed bucket represents such a high share of ICE vehicles, it is no surprise that the results in the paper for products assigned to the mixed bucket track closely with products assigned to the ICE bucket, with slight differences being driven by the hybrids and BEVs.

Table B1. Share of Sales within Mixed Bucket by Powertrain Technology and Model Year

Model Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
ICE	96.40	97.39	96.80	96.04	95.57	96.66	95.30	94.34	93.22	90.66	90.74	85.28	81.65	94.71
Hybrid	3.60	2.60	3.18	3.79	3.99	2.91	3.69	4.63	5.05	7.44	7.89	11.90	14.44	4.56
Plug-in Hybrid	0.00	0.00	0.00	0.08	0.29	0.22	0.72	0.80	1.51	1.61	1.12	2.40	3.23	0.57
BEV	0.00	0.00	0.02	0.09	0.15	0.21	0.27	0.19	0.17	0.23	0.22	0.37	0.63	0.15
Fuel Cell	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.05	0.05	0.02	0.04	0.04	0.01

Note. The following table reports the share of sales by powertrain technology within the mixed bucket from MY2010 to MY2022. Because there are cases where a product is offered with multiple powertrains, we cannot distinguish if they are ICE, hybrid, or electric and, as a result, categorize them in the mixed powertrain bucket. This table utilizes sales data from Wards to show how the share of sales is distributed across different powertrain technologies within the mixed bucket across MY2010 to MY2022. The total column takes the total number of unit sales within the mixed bucket from MY2010 to MY2022 and calculates the share across the powertrain technologies.

Source: Authors' calculations based on data from Wards Intelligence and Autocount

Once concern with the mixed bucket could be that a nontrivial share of all BEVs are assigned to the mixed bucket. We tabulate the share of BEV sales that are assigned to either the BEV or mixed bucket in Table B2. We find across all model years that the vast majority of BEV sales are assigned to the BEV bucket.

Table B2. Share of BEV Sales assigned to BEV or Mixed Powertrain Bucket, by Model Year

Model Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
BEV	100.00	98.89	91.28	89.36	87.32	86.27	85.42	90.24	94.53	95.93	95.41	94.75	95.06	92.46
Mixed	0.00	1.11	8.72	10.64	12.68	13.73	14.58	9.76	5.47	4.07	4.59	5.25	4.94	7.54

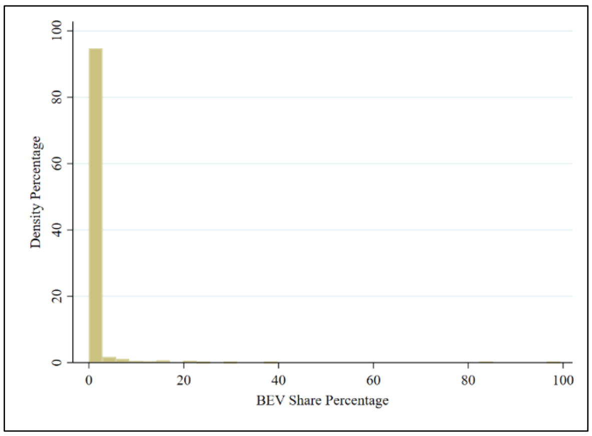
Note. The following table reports the share of BEV sales assigned to either the BEV or mixed powertrain bucket from MY2010 to MY2022. The sales data comes from Wards Intelligence data center. The total column takes the total number of BEV unit sales from MY2010 to MY2022 and calculates the share across the powertrain buckets.

Source: Authors' calculations based on data from Wards Intelligence and Autocount

To see if we are assigning a nontrivial share of BEVs to the mixed bucket at the product level, we calculate the percentage share of total sales that are BEVs for each product in the mixed bucket. Panel A of Figure B1 shows that over 95% of products in the mixed bucket have a share of BEV sales that is less than 5%. Panel B of Figure B1 shows this share by MY for the observation period. There are 7 mixed products in the dataset with a share of BEV sales greater than 20%: the MY2014, MY2015, MY2018, and MY2019 Kia Smart Fortwo; the MY2020-MY2021 Kia Niro; and the MY2022 Volvo XC40. These are not high-volume products, thus we are not concerned with these products being assigned to the mixed bucket influencing our results.

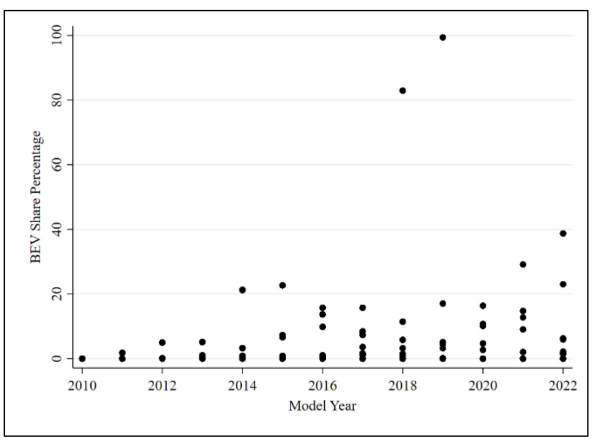
Figure B1. Share of BEV Sales of Mixed Products

Panel A. Share of BEV Sales Histogram



Note. The following figure shows the histogram of the share of total sales of each mixed product that are BEVs.

Panel B. Share of BEV Sales Scatter Plot, by Model Year



Note. The following figure shows the scatter plot of the share of total sales of each mixed product that are BEVs for MY2010 to MY2022.

Source: Authors' calculations based on data from Wards Intelligence and Autocount

Appendix C. Lower Bound VMT Exercise

Our measure of VMT for each product-age observation is the mean odometer reading of all used registrations. This means that we only observe odometer readings at the point of transaction. Not all vehicles are resold during the observation period, however. It seems reasonable to assume that the resale decision for a vehicle is positively correlated with its usage (mileage). To establish how the omission of vehicles that don't transition to the used status during the observation period might affect our measure of VMT, we compare our measure to Davis (2019) in order to estimate a lower-bound of our VMT measure.

Davis (2019) utilizes data from the 2017 National Household Travel Survey (NHTS) to estimate differences in VMT between vehicles of different powertrains. The NHTS survey considers vehicles for each household in the survey, regardless of new or used. Within the NHTS, each respondent is asked to fill out an "Odometer Mileage Record Form." Davis constructs a measure of the average number of miles driven per year by dividing this measure by the age of the vehicle. The mean VMT per year by powertrain technology from Davis (2019) is reported in Table C1.

We reconstruct Table C1 to reflect the mean VMT per year values across our four powertrain buckets in Column 2 of Table C2 by dividing our measure of VMT by age for each product-age observation registered in 2017 for all ages. Finally, we take the mean VMT per year across all four buckets, weighting by used registrations. The weighted mean is reported in Column 3 of Table C2. These means are also reported in Figure C1. This exercise shows that our measure of annual VMT appears to slightly overestimate usage when compared to the results from Davis (2019).

Table C1. VMT per Year Estimates from Davis (2019)

	Number of Observations	Mean
All-Electric Vehicles [BEV]	436	6,300
Plug-in Hybrids [Hybrid]	426	7,800
Gasoline/Diesel Vehicles [ICE]	203,988	10,200
Conventional Hybrids [Hybrid]	4,443	11,800

Source: Davis (2019)

Table C2. VMT per Year Comparison

	Davis (2019)	Bognar et al (WP)
ICE	10,200	14,880
Mixed	10,220	14,860
Hybrid	11,450	12,950
BEV	6,300	8,060

Source: Wards Intelligence, Autocount, and Davis (2019)

Given this comparison, we construct a lower bound estimate of our VMT measure. To do this, we utilize the fact that UPR is conceptually defined as the percentage of new vehicles that have been resold. This means that $(1 - UPR)$ reflects the percentage of unsold vehicles. We can then perform the following calculation to recover an aggregate lower bound estimate of our VMT measure. First, we sum the number of new and used registrations, and the used odometer readings over all ages and our four powertrain buckets. Let n be the pooled number of new registrations for bucket b at age a, u be the pooled number of used registrations for bucket b at age a, and $(used\ sum)_{ba}$ be the pooled sum of used odometer readings for bucket b at age a. We estimate the number of unsold vehicles by:

$$(1 - UPR)_{ba} * (n)_{ba} = unsold_{ba}$$

We can then estimate the sum of odometer readings from these unsold vehicles for bucket b at age a, $(unsold\ sum)_{ba}$, by multiplying $unsold_{ba}$ by imputed VMT per year estimates from Davis (2017) $imputed_b$ and age a. Here, $imputed_b$ is 10,200 for the ICE bucket, 10,220 for the mixed bucket, 11,450 for the hybrid bucket, and 6,300 for the BEV bucket. The equation is modeled by:

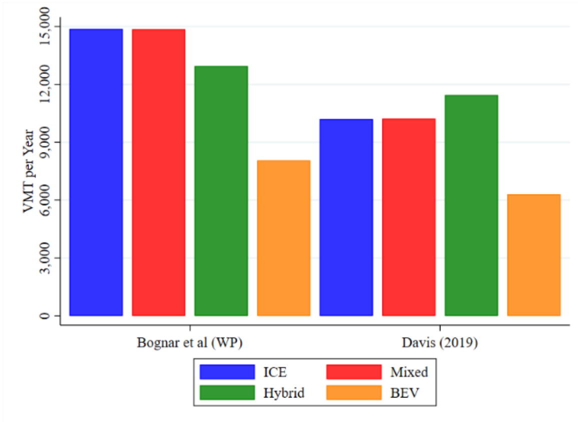
$$(unsold_{ba}) * imputed_b * a = (unsold\ sum)_{ba}$$

Finally, we can estimate the lower bound VMT by

$$\frac{(used\ sum)_{ba} + (unsold\ sum)_{ba}}{u_{ba} + unsold_{ba}} = lower\ bound\ VMT$$

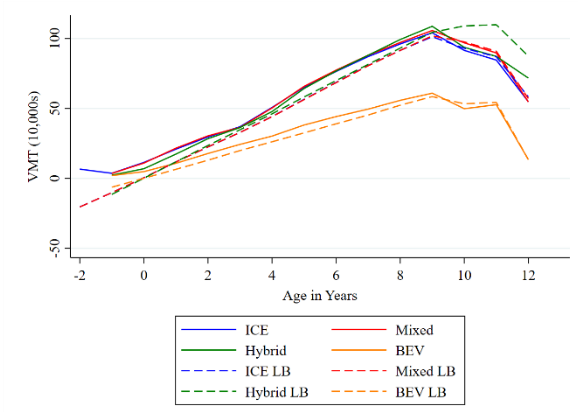
Figure C2 plots the lower bound VMT with our measure of VMT. It shows that the counterfactual exercise results in a collective shift downward in VMT across all four powertrain buckets by moving from our data to the NHTS survey-based data, which samples over all vehicles.

Figure C1. VMT per Year Comparison



Source: Wards Intelligence, Autocount, and Davis (2019)

Figure C2. Lower Bound VMT over Age



Source: Authors' calculations based on data from Wards Intelligence and Autocount