Research Report – UCD-ITS-RR-17-25

A Multi-Model Approach to Generating International Electric Vehicle Future Adoption Scenarios

October 2017

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3EVS30 Symposium
Stuttgart, Germany, October 9 - 11, 2017

A multi-model approach to generating international electric vehicle future adoption scenarios

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Summary
The widespread adoption of electric vehicles is an essential transition towards reducing the climate impact of the transportation sector. As the international community seeks to decrease carbon emissions into the future, the impact of electric vehicles is still highly dependent on its success in displacing conventional internal combustion engine vehicles. Our work contributes to a large body of literature forecasting the electric vehicle market. We leverage a unique dataset of new vehicle registrations from 2005 through 2015 to calibrate several models for the purposes of forecasting. The data was acquired in a joint venture with the International Energy Agency and spans 39 countries, 4,771 models, 503 manufacturers, and over 500 million new vehicle registrations from 2008 through 2015. Due to the inherent uncertainty in forecasting models, we take a three-pronged approach by constructing 1) discrete choice modeling approach, 2) diffusion of innovation approach, and 3) regression of trends approach. We attempt to understand what levels of adoption will be seen over the next 40 years through various scenarios of policy intervention, natural price decreases in the technology, and a number of other attribute changes. Importantly, we are able to observe different responses in various international markets to a number of different parameters.
Keywords: BEV, deployment

1 Introduction

The challenges of climate change have provided tremendous motivation to mitigate carbon emissions around the world. The transportation sector represents not only a massive contributor to carbon emissions but it is also a rapidly growing sector as developing countries begin to catch up to modern transportation technologies. Fortunately, automakers have been introducing electric vehicles in the light-duty passenger vehicle sector as a possible mitigation solution. The electric vehicle (EV) market across the world has grown by a remarkable amount over the last decade. From essentially no commercial vehicles on the market in 2007, there are a cumulative 2 million electric vehicles on the road globally in 2016 with over 770,000 vehicles sold in that year alone[1]. However, this success story is mitigated by how far electric vehicles have to go: the new technology only represents 0.86% of global vehicle sales. The goal of this

[1] The Electric Vehicle World Sales Database http://www.ev-volumes.com/country/total-world-plug-in-vehicle-volumes/

work is to understand the factors driving these sales such as policy mechanisms, infrastructure requirements, and the vehicle attributes themselves to see how scenarios of these variables can be leveraged to understand how electric vehicles may develop far into the future.

Our research can be distinctly divided into two stages: first, developing and estimating econometric models of the current EV sales in the context of 35 country-level markets and second, using these model structures to project EV sales into the future using a scenario approach. In the first stage, we have used a large database with observations of current and historical sales and a range of vehicle attributes to build several models of different types to attempt to understand various aspects of the growth of the technology. By using three separate modelling approaches we can compare and hopefully minimize the modeling error intrinsic to each process such that we can identify robust trends that arise consistently across the three models. In the second stage we project EV sales worldwide to 2050 across a number of scenarios using each of the three models. This second stage relies on the first stage to properly calibrate the parameters responsible for the growth of the technology. However, our projections also rely on assumptions regarding changes in future parameters in order to make projections for the adoption of EVs into the future. In order to demonstrate robustness, we apply these assumptions across a variety of models to establish consistency in the results. The following sections of this report are structured as follows: Section 2 covers our database development efforts, Section 3 outlines our three model methodology, Section 4 presents results and Section 5 provides a discussion of these results.

2 Data

In cooperation with the IEA, UC Davis acquired a large international vehicle registrations database (from HIS Automotive) to conduct our study. In this section we provide a summary overview of the data both in totality and as a subset of electric vehicles. The IHS data were first supplemented by staff at the International Energy Agency with additional information on vehicle attributes including the axle configuration, vehicle drive type, engine size, number of cylinders, power of the engine, fuel type, transmission type, turbo capabilities, price, segment, curb-weight, footprint, fuel efficiency/emissions rates, and vehicle range. The final cleaned dataset consists of over 900,000 vehicle models accounting for a total of 500 million new vehicle sales over the span of 8 years and 39 countries.

The total registrations across the full dataset can be seen in Figure 1 separated by country and divided by vehicle fuel type. By far the two largest vehicle markets are the United States and China, both of whom have vehicle sales reaching nearly 120 million vehicles over the span of 8 years. The next closest country in terms of market size is Japan, which sold about 40 million vehicles over the same period of time. The majority of country vehicle sales are dominated by petrol (or gasoline) vehicles. Exceptions include the United Kingdoms, France, Italy, Thailand, Turkey, and Spain, which sell more diesel vehicles than petrol vehicles as well as Brazil whose vehicles primarily consist of flex fuel vehicles. Against the full market of vehicles, electric vehicles representing substantially less than 1% of sales are unobservable in Figure 1.

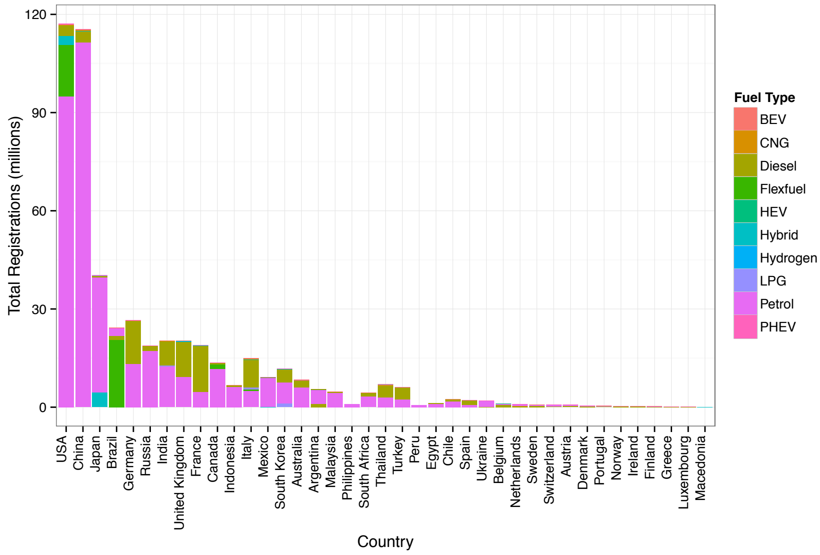

Figure 1: Total registrations in IHS/IEA data separated by country and fuel type vehicle technology spanning 2005, 2008, and 2010 through 2015. Of the over 500 million vehicles registered, nearly half are from USA and China. Petrol (gasoline) vehicles represent the majority of cars sold in nearly every country except for a handful of countries whose diesel vehicle sales are higher and Brazil where the majority of vehicles sold are flex fuel vehicles.

The dataset captures a total of 1.1 million new electric vehicle registrations across both battery electric vehicles (BEVs) and plug-in hybrid vehicle (PHEVs) technologies. Approximately 170 unique vehicle models represent the full set of technologies over 34 of the 39 countries included in the data. The distribution of electric vehicle models is not uniform at the international scale, while certain vehicle models can be found in several countries it is not uncommon for many vehicle models to be exclusive to a single country or a small subset of countries.

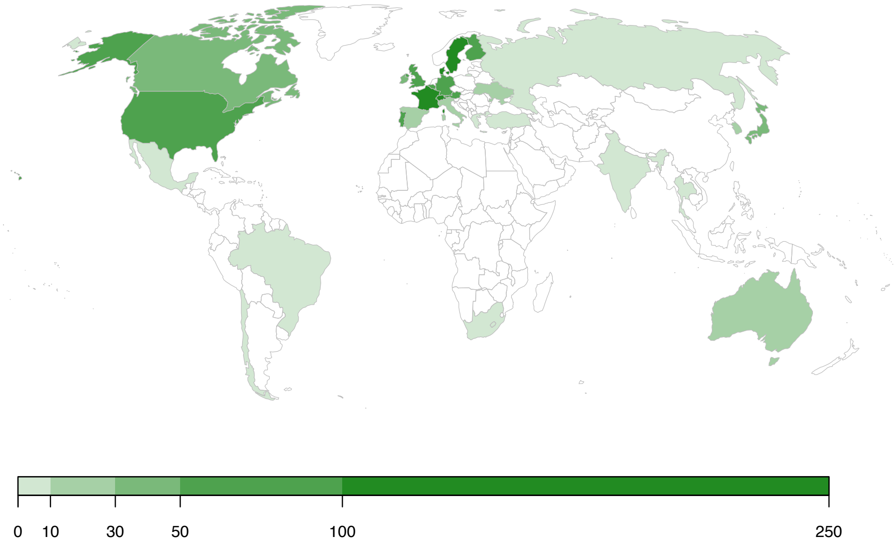

Figure 2: Spatial distribution of electric vehicle sales (both BEVs and PHEVs combined) in 2015 worldwide based on density of registrations (number of registrations per 10,000 conventional vehicles sold). All shaded countries contain sales data for EV registrations in 2015. Norway is a special case with 6,000 EVs sold per 10,000 conventional vehicles and is not included in this figure.

One important aspect of electric vehicle adoption is the diversity in vehicle options for the technology. We observe a strong correlation between the number of EV models and their total adoption. The number of electric vehicle models in the market across the world has been growing over time with nearly 90 BEV models and 40 PHEV models available at the end of 2015. Similarly, the two technologies are compared to traditional hybrids that have been available over a decade longer than the new electric vehicle technologies.

The rate of growth in terms of model availability has been significantly higher for both BEVs and PHEVs than hybrids.

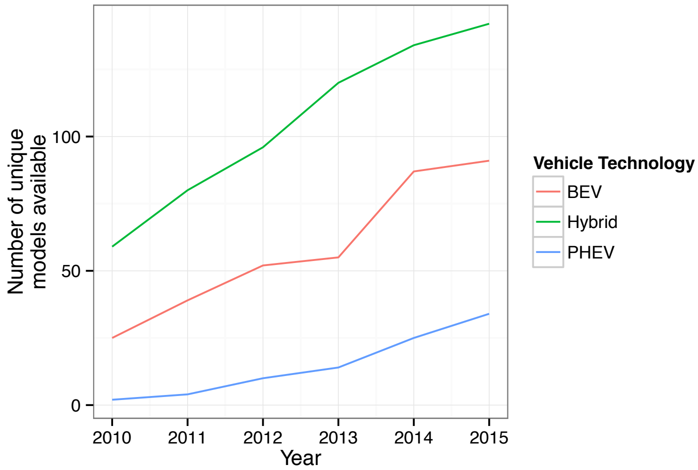

Figure 3: Growth in the number of unique vehicle models available for hybrid, plug-in hybrid, and battery electric vehicle technologies over time across 39 countries.

In addition to the number of vehicle models available for sale on the market, the coverage of electric vehicle models across vehicle segments is imperative to penetrate across different market groups for wider adoption. While a large number of registrations have occurred, the adoption has mainly occurred in smaller segment sizes, especially when comparing the distribution of sales to the full population distribution. The growth of electric vehicles in larger segments will likely improve as more models are made available in their respective vehicle size classes.

One additional attribute of interest for electric vehicles is their all-electric range. The range of an electric vehicle is often considered a limiting factor for the widespread adoption of the technology with worries about the capabilities of the technology under this attribute being referred to as "range anxiety". The ranges for BEVs vary tremendously from below 100 km to as high as 390 km, covering a wide variety of transportation applications. PHEV ranges are significantly lower ranging between 10 and 100 km. In addition to the simple summary statistics about electric vehicles, we are able to take advantage of the relatively high resolution of the IEA/IHS data to approach modeling in several different ways. We describe the various modeling methods in the following section.

3 Methods

There are a number of projection methods that are used to estimate future scenarios of technology adoption and each have corresponding strengths and weaknesses due to the assumptions associated with their respective modeling techniques. In order to reduce this specific modeling error, we approach our projection by using three distinct models: a choice model, diffusion of innovation model, and regression of trends model. The fundamental characterization of each respective model can be described as follows: a belief that consumers will rationally choose from a set of products based on their attributes, a belief that a specific technology will be adopted in a particular manner, and a belief that the success of a technology is associated with a number of factors (both intrinsic to the product and external to the product). The primary goal of our work is to attempt to find consistency across different models to demonstrate robustness in our findings and projections. In the following sections, we describe each of the approaches in detail.

3.1 Consumer choice model approach

In our consumer choice model approach, we have used a standard discrete choice process. In this model, we attempted to simulate consumers' decision-making process about selecting a single product among a set of discrete choices, in this choice the decision to purchase a vehicle among a population of available vehicle models. The consumer chooses based on attributes of the product in comparison to other products. The desirability of attributes are standardized to units of utility, specifically the utility for a vehicle model *i* which is represented as:

$$u_i = \sum_j \beta_j X_{ij} + \zeta_i + \varepsilon_i \tag{1}$$

Where j is the index of vehicle attributes being considered by the consumer and X_{ij} represents the values of each of the respective vehicle attributes. In our model, we included the vehicle attributes in set j={price, emissions rate, vehicle make, fuel type, vehicle segment, vehicle range, drive type, engine power, and engine size}. The parameter ζ represents the alternative specific constant. This term is a constant that represents the utility specific to the vehicle model not captured by the other attributes. Our model was run separately for each of the 39 countries. We assumed that the social and cultural aspects of each country lead to different responses to the value in the various vehicle attributes.

In order to estimate the values of β_j which translate the attributes into utility space, we employed a typical logit procedure where the market share of vehicle i is determined as follows:

$$S_i = \frac{e^{u_i}}{\sum_k e^{u_k}} \tag{2}$$

The β_j parameter was then estimated via a maximum-likelihood estimation procedure that attempts to match the predicted market share to the actual market share by varying the β_j parameters. We were then able to estimate the respective market share resulting from variation in the input attributes. X_{ij} can be adjusted to predict market shares of specific vehicle models as the price, range, and other attributes of electric vehicles changes over time.

3.2 Diffusion of innovation approach

The diffusion of innovation is widely studied field. The basis of this field is the assumption that the adoption of any technology follows a general growth trend that is sigmoidal in shape. While the specific parameters of the adoption curve can differ from one technology to another, the general shape remains the same. As a result, we were able to take advantage of this assumption and calibrate the curve against the available data. One of the earliest diffusion models is the Bass model as shown in Equation (3).

$$S(t) = m\frac{(p+q)^2}{p}\frac{\exp(-(p+q)t)}{\left(1+\frac{q}{p}\exp(-(p+q)t)\right)^2} \tag{3}$$

In the Bass diffusion curve model, the sales S in a year t is determined by a number of parameters including the market potential m, the coefficient of innovation p, and the coefficient of imitation q. The model assumes that adopters are classified as innovators and imitators and the level and timing of adoption is dependent on the degree to which each of the adopters uptakes the technology. Our general approach was to separately estimate p and q for each country based on their respective sales of electric vehicle technology in their vehicle markets. Once the parameters were estimated, projections based on the year of adoption were made to generate scenarios of adoption in the future.

In order to align assumptions across models, we also investigated diffusion models that use exogenous explanatory variables. One such model is the Generalized Bass Model (GBM), which incorporates marketing variables in new product diffusion:

$$h(t) = (p + qF(t))x(t) \tag{4}$$

where

$$x(t) = 1 + \beta_1\frac{\partial P(t)}{\partial t} + \beta_2\frac{\partial A(t)}{\partial t} \tag{5}$$

The GBM allows for the incorporation of a price variable $x(t)$, which can help to calibrate the model based on uptake across various nations across the globe. In addition, the price can be adjusted in projections based on policy scenarios and expectations of price changes in the technology. The additional variable can significantly increase the computational complexity of the estimation procedure (which is highly non-linear). We estimated the parameters using Maximum Likelihood Estimation (MLE), simulating a large number of starting points until a feasible solution is converged on.

3.3 Regression of trends approach

The regression model examines trends at several levels of aggregation. Unlike the discrete choice model, the regression model does not operate at the vehicle model level but we aggregated the data up to the segment and vehicle technology level for analysis. The average vehicle price by fuel type and country varies by a substantial amount, as high as $700,000 for certain vehicle aggregations. Meanwhile, the number of models can vary in certain countries that only have a single vehicle model for a particular vehicle technology (often PHEVs or flex fuel vehicles) up to 587 vehicle models for typical gasoline vehicles. The model at the fuel type level *f* includes petroleum (gasoline), hybrids, flex fuel vehicles, LPG, diesel, CNG, hydrogen, BEVs, and PHEVs and is represented as:

$$\begin{aligned}\log\left(s_{fct}\right) = \beta_1 \text{price}_{fct} + \beta_2 \text{emrate}_{fct} + \beta_3 \text{numModels}_{fct} + \\ \beta_4 \text{country}_c + \beta_5 \text{fuel}_f + \beta_6 \left(\text{country}_c * \text{fuel}_f\right) + \sum_i \alpha_i C_{ict} + \varepsilon_{fct}\end{aligned} \quad (6)$$

Where other indexes include country *c* and year *t*. Additionally there are a number of country specific variables *i* captured in the regression including the country's population, gas price, GDP, and unemployment. The remainder of the vehicle attribute variables were averaged over their respective indexes. We also included a more finely segregated model broken down by both vehicle segment and fuel type:

$$\begin{aligned}\log\left(s_{fsct}\right) = \beta_1 \text{price}_{fsct} + \beta_2 \text{emrate}_{fsct} + \beta_3 \text{numModels}_{fsct} + \beta_4 \text{segment}_s \\ \beta_5 \text{country}_c + \beta_6 \text{fuel}_f + \beta_7 \left(\text{country}_c * \text{fuel}_f\right) + \sum_i \alpha_i C_{ict} + \varepsilon_{fct}\end{aligned} \quad (7)$$

The models are identical with the exception of the addition of the vehicle segment variable and the distinction of vehicle attributes across the segment variable. The macroeconomic variables of population, gas price, GDP, and unemployment remain the same as their values are only dependent on the country of origin and not on the aggregation of vehicle data.

3.4 Model projection scenarios

Our approach has been to generate several projection scenarios based on assumptions of electric vehicle price reductions, vehicle model availability, and driving range. While the underlying assumptions are rather simplistic, they allow us to provide a direct comparison between the three models by providing a consistent basis of future EV attributes necessary to generate the projections. The scenarios of price reduction are a generic change in price that can result from cheaper production costs (due to decreases in battery costs or more efficient manufacturing) or direct policy incentives. The price reductions range from $5,000 up to $15,000 on average for an electric vehicle (either BEV or PHEV). For each of the respective scenarios, vehicle prices decrease linearly by $5000, $10000, and $15000 by 2040 with 10%, 20%, and 50% model saturation of the market by 2040 as well. The vehicle range increases linearly to a 50 km, 100 km, and 150 km for each respective scenario.

4 Results

4.1 Model fitting

4.1.1 Consumer choice model

In the series of discrete choice models developed as in Equation (1), we are able to obtain results for 31 countries, four of which are shown in Table 1. While the full dataset contains 39 countries, only 34 contain electric vehicles and three of which were computationally intractable. There is a tremendous amount of variation in the valuation of different vehicle attributes from country to country that can be attributed to a number of factors including differences in vehicle market, social and cultural differences, government policy, and fuel availability to name a few.

While the odds-ratios in Table 1 are not immediately decipherable, we note that the signs and magnitudes for the majority of the countries are sensible. For example, in the United States the coefficients on both price and emissions rate are both negative indicating that all else equal purchasers of vehicles desire cheaper and cleaner/more fuel efficient vehicles. When looking at the relative coefficient sizes under fuel types, it may seem counterintuitive that relative to a battery electric vehicle baseline, petrol vehicles are actually negatively favored. However, once the range of the vehicle is taken into account, traditional gasoline vehicles come out much farther ahead in terms of consumer utility. On the flipside, this also means that a comparably ranged battery vehicle would actually be favored over traditional gasoline vehicles (in the United States). Other vehicle attributes we control for but whose coefficients are not displayed include the vehicle manufacturer, vehicle segment, engine power, engine size, and alternative specific constants for each individual vehicle model.

One significant issue that manifested in several countries was multicollinearity between price, vehicle emissions rate, and range of the vehicles. In about a sixth of the countries, the signs and magnitudes of coefficients were illogical. For example, in China the coefficients on price and emissions rate are both positive while the coefficient on range is negative. As a result, the model would predict consumers to favor more expensive, dirtier/less fuel efficient, and shorter ranges.

Table 1: Discrete choice logit model representative results for 4 of 31 countries. Coefficients represent odds-ratio of probability of choice corresponding to a vehicle model.

Variable	United States	China	United Kingdom	Norway
Price ($100,000)	-1.17***	1.55***	-1.05**	-0.839**
	(0.00507)	(0.00454)	(0.0116)	(0.0358)
Emissions Rate (mg CO_2/km)	-4.61***	0.273***	-24.8***	-1.6***
	(0.0163)	(0.0196)	(0.0584)	(0.186)
Range (m)	24.1***	-2.15***	67.6***	19.7***
	(0.223)	(0.0916)	(0.596)	(0.363)
Fuel Type				
BEV (baseline)	0	0	0	0
	(0)	(0)	(0)	(0)
CNG	NA	10.1***	NA	-10.8***
		(0.0285)		(0.373)
Diesel	-9.91***	12.6***	-19.9***	-7.39***
	(0.267)	(0.0436)	(0.176)	(0.11)
Flexfuel	-4.22***	0.338***	0.84***	NA
	(0.0754)	(NA)	(2.5e-10)	
Hybrid	-5.35***	11.2***	-21.4***	-6.44***
	(0.0755)	(0.0256)	(0.177)	(0.113)
Petrol	-3.28***	13***	-19.5***	-8.25***
	(0.0754)	(0.0252)	(0.176)	(0.110)
PHEV	4.03***	11.6***	8.48***	2.22***
	(0.0295)	(NA)	(0.0839)	(0.0614)
Manufacturer	x	x	x	x
Segment	x	x	x	x
Engine Power	x	x	x	x
Engine Size	x	x	x	x
ASC (by model)	x	x	x	x

The relative coefficients on price between countries are displayed in Figure 4(a). The countries are ordered in terms of decreasing price sensitivity going from left to right. In our model, the relative utility gain from a decrease in price of $100,000 ranges from -10 to 0. The price coefficient provides a baseline level of utility for comparison for the other attributes. For example, for the United States an emissions rate coefficient of -4.6 translates roughly to a willingness to pay to decrease vehicle emissions (or increasing fuel economy) of approximately $394 per g CO_2/km. Unfortunately, the collinearity issue mentioned before also reveals itself here. Twelve countries have a price coefficient greater than 0 (hence positive value coefficients) and are likely the result of a mis-specified model.

Similarly, we display the relative coefficients on vehicle range between countries in Figure 4(b). A positive value on the coefficient is expected for vehicle range as all else equal a consumer would seek to purchase a vehicle with greater range. The variation in range preference is still quite substantial, ranging from -200 to over 100 in equivalent utility. However, the majority of countries have a smaller span with only a handful of countries greater than +/-20 from 0. We note that there is a distinct overlap in problematic countries in the price and range coefficients (China, France, Spain, Mexico, etc.).

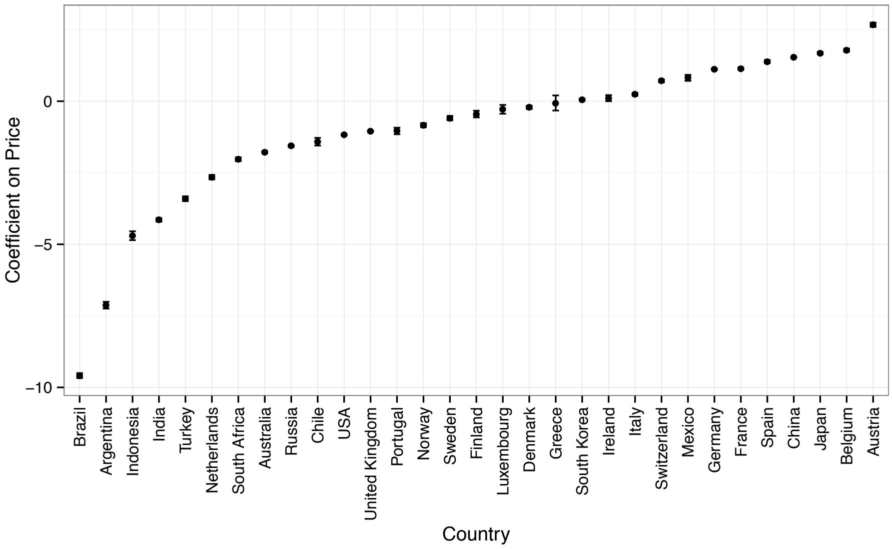

Figure 4(a): Relative price ($100,000s) odds-ratio coefficients from discrete choice logit models run independently for 31 countries. Price sensitivity decreases from left to right.

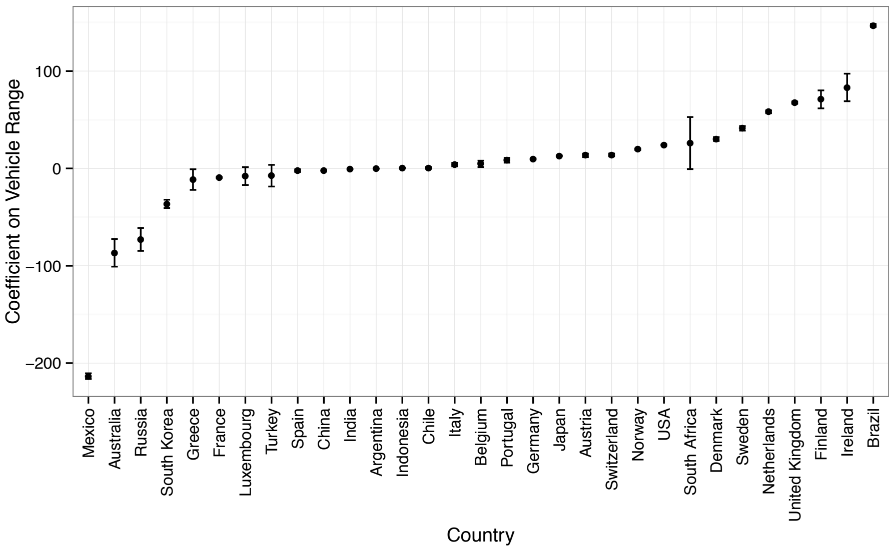

Figure 4(b): Relative vehicle range (m) odds-ratio coefficients from discrete choice logit models run independently for 31 countries. Preference for vehicle range increases from left to right.

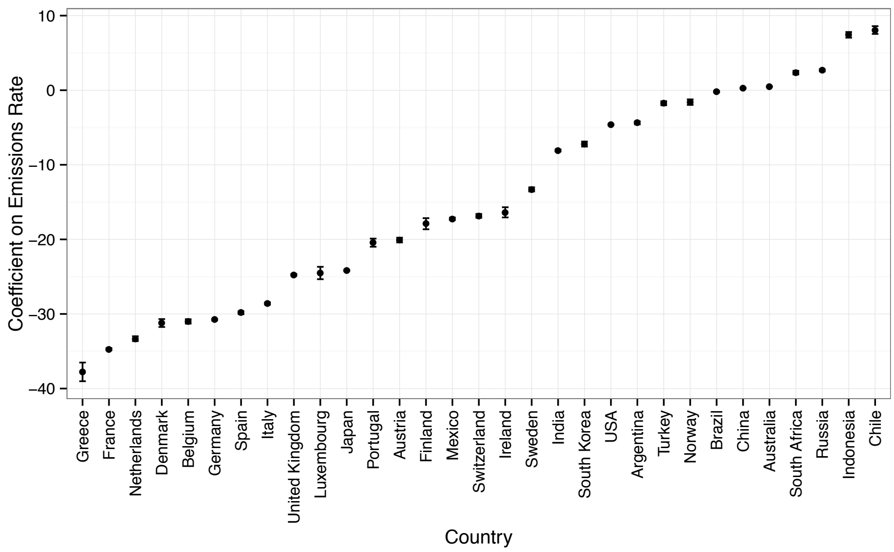

Figure 4(c): Relative emissions rate (mg CO_2/km) in odds-ratio coefficients from discrete choice logit models run independently for 31 countries.

In Figure 5(c), we display the relative utility from each vehicle fuel technology relative to a 0 baseline for traditional gasoline vehicles. The points actually represent a combination of the coefficients of fuel technologies derived from the model and the coefficient on range multiplied by the average vehicle range for each respective fuel technology. The emissions rates are directly correlated with fuel efficiency and preference for efficiency can be inferred as inversely proportional to the emissions rate. The sensitivity to emissions rate decreases from left to right (preference for fuel efficiency decreases left to right). For traditional vehicles the full range is assumed to be approximately 400 kilometers while the ranges on PHEVs and BEVs are noticeably smaller. For certain fuel technologies such as CNG or LPG, the representation is slightly smaller due to limited availability on the market for many countries but BEVs, diesels, hybrids, and PHEVs seem to be widely available across the panel of countries in the data.

Most alternative fuel vehicle technologies across most countries have negative coefficients, indicating a lower preference in comparison to gasoline vehicles. While exceptions to the rule are observed (higher preference for hybrids and electric vehicles in Norway and Sweden), most consumers still consider alternative vehicles to be inferior to petrol vehicles. This serves as an inherent “handicap” in our projections for electric vehicle adoption. Notably the choice model itself has no ability to capture changing consumer sentiments to the technologies over time.

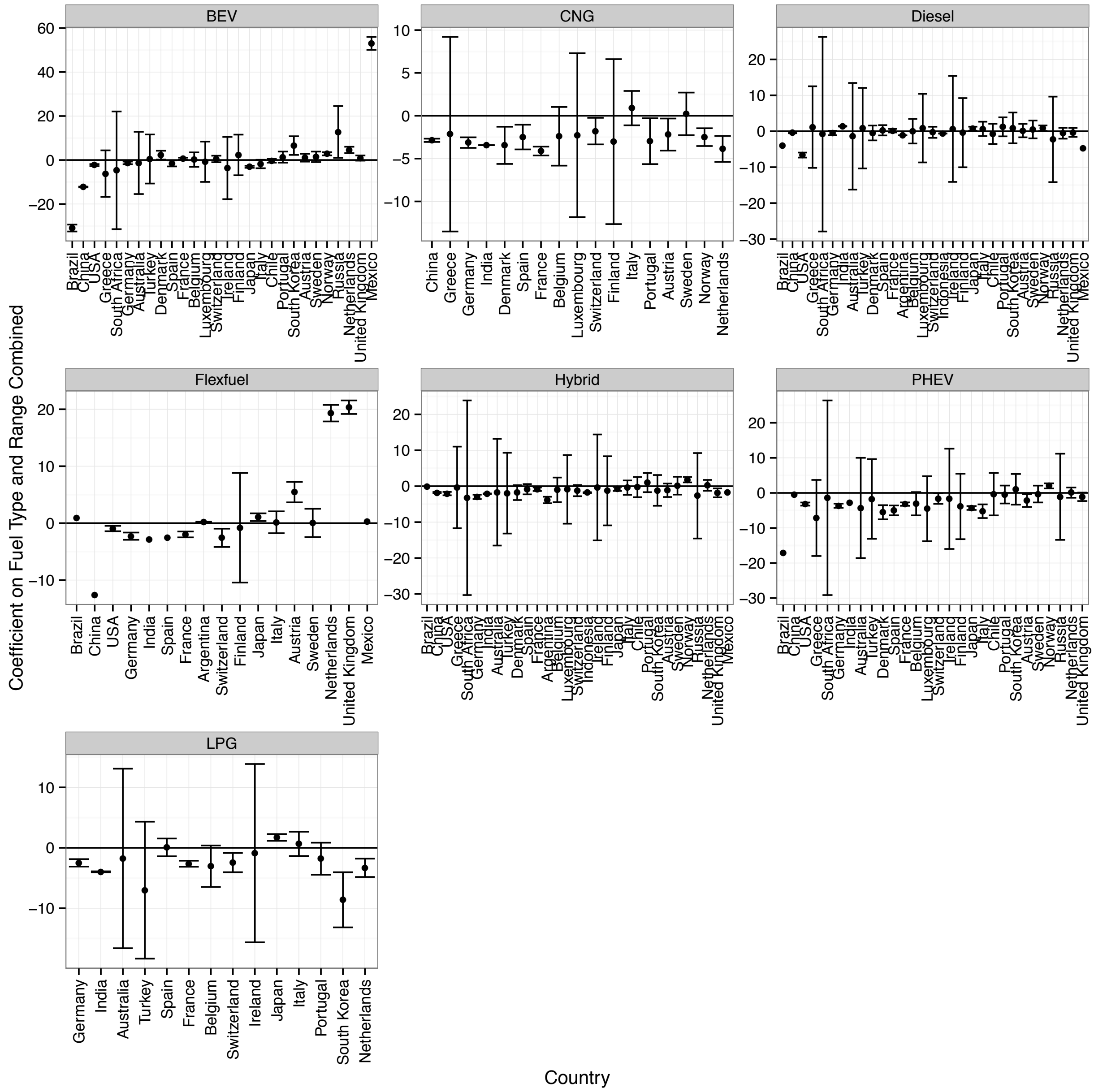

Figure 5: Coefficients representing relative utility of combined fuel technology and vehicle range relative to traditional petrol (gasoline) vehicles (baseline at 0). The points combine the results of the choice model for fuel type with the coefficients on range scaled to the average vehicle range in each respective vehicle fuel technology.

The discrete choice approach provides a simple method to simulate the growth of a technology through a model of car buyers selecting a product amongst its competitors in the market. While there are a number of inconsistencies in results from certain countries, we find that a large portion of countries provide coefficient results in line with our expectations. It is not surprising to find a large amount of variation in valuation of vehicle attributes between countries and in fact helps to explain intrinsic differences between markets in different countries. There are a number of potential modeling issues specific to a logit based discrete choice approach but these results will be tempered by comparison across the diffusion and regression models to follow in sections 4.1.2 and 4.1.3 respectively.

4.1.2 Diffusion of innovation model

We chose to use a basic Bass diffusion model to project the adoption of electric vehicles in the future. Our models are calibrated separately for BEVs and PHEVs as well as independently for every country with over 3 years of sales for each of the respective technologies. The results of the calibration are shown in Figure 6 for BEVs. The figures display the relative size of coefficients p and q among different countries. The coefficient of innovation p describes the initial uptake of the technology with the highest values appearing for Japan, USA, and France for BEVs and Japan, USA, and Canada for PHEVs. However, we do note that the coefficient is quite small compared to other technologies whose value is usually around 0.03. This indicates that the initial uptake of electric vehicles is significantly smaller than other technologies in the literature. Interestingly enough, the reference point for the coefficient of imitation q is 0.38 and is lower than quite a few of the estimated coefficient values in both BEV and PHEV technologies. Once the technology begins to pass the initial adoption phase, the Bass model estimates that a relatively rapid uptake of EVs will occur relative to other technologies. China has very high q values in both the Bass models for BEVs and PHEVs, likely due to their rapid adoption of both technologies in the recent years.

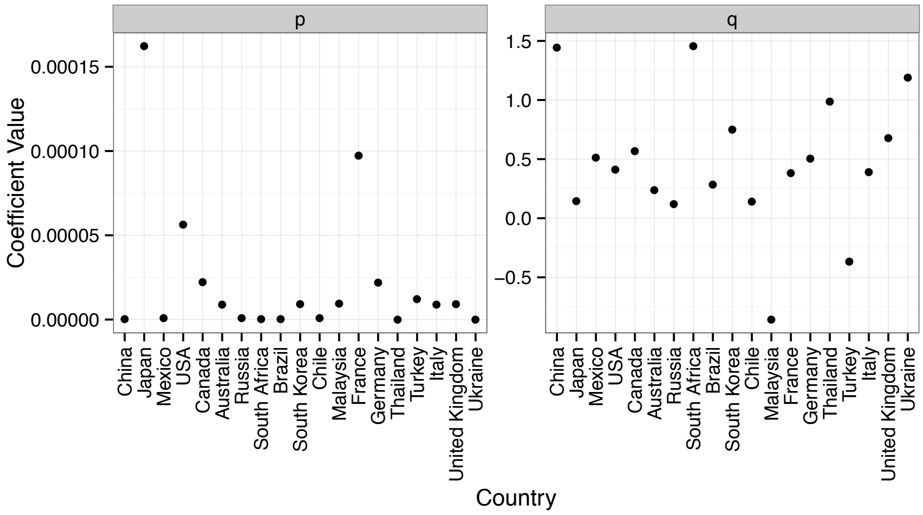

Figure 6: Coefficients from Bass model calibrated to historical sales of full battery electric vehicles. The p coefficient describes the coefficient of innovation, the higher this value the greater the initial uptake of the technology when initially offered. The q coefficient describes the coefficient of imitation, the higher this value the greater the growth of the technology after the "first-takers" have been saturated.

Using the coefficients p and q and applying them to Equation (3), we are able to make basic projections of technology saturation. These estimates can be found in section 4.2.

4.1.3 Regression models

A set of basic linear regression models is run on two separate data aggregations from the main database. The first set of data is aggregated to the vehicle fuel technology and country level where all attributes in the model are grouped (sales-weighted averages for numeric variables) for analysis. Table 2 shows the set of regression results based on Equation (6). The coefficients are all logical with negative coefficients on undesirable traits such as price and emissions rate, and positive coefficients for vehicle range and number of available models for a given technology. The price coefficient ranges describe an effect of 0.4-0.8% decrease in the sale of a vehicle group corresponding to a $1,000 increase in price on average. Similarly, the emission rate describes a 1.4-1.6% increase resulting from a decrease in emissions rate of 1 g CO_2/km on average. There are a number of other factors that can assist in the growth of EV technologies, particularly the increase in ranges of the vehicles (a 1.6-2.1% increase per km) and the number of available vehicle models (0.3-0.8% increase per model). The regression model includes dummy variables for the country as well as interactions between both fuel type and country as well as fuel type and gas prices but these effects are controls whose explicit coefficients are excluded from Table 2.

Table 2: Regression results on *log(registrations)* with data divided by vehicle fuel technology

Variable	(1)	(2)	(3)
Price ($)	-7.65e-6***	-2.89e-6**	-4.29e-6**
	(1.14e-6)	(1.42e-6)	(1.78e-6)
Emissions Rate (g CO_2/km)	-0.016***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.002)
Range (km)	0.019***	0.021***	0.016*
	(0.005)	(0.005)	(0.008)

Number of Models	0.008***	0.003*	0.005**
	(0.001)	(0.001)	(0.002)
Population	-	-	4.43e-10
			(1.12e-8)
GDP	-	-	2.47e-13
			(1.46e-13)
Unemployment	-	-	-0.063
			(0.075)
Fuel Type			
BEV (baseline)	0	0	0
	(0)	(0)	(0)
CNG	-4.459**	-11.352***	-10.032*
	(1.644)	(2.189)	(5.886)
Diesel	0.533	-2.362	2.373
	(1.669)	(2.508)	(3.901)
Flexfuel	-0.638	0.402	-4.223
	(1.722)	(2.521)	(3.875)
Hybrid	-10.642***	-11.833***	-3.599
	(2.589)	(1.952)	(3.834)
LPG	-2.364	-10.621***	2.398
	(1.691)	(2.479)	(4.77)
PHEV	3.83***	4.084***	5.889
	(0.844)	(1.065)	(4.497)
Petrol	1.392	1.135	3.959
	(1.703)	(1.899)	(3.927)
Country	x	x	x
Country*Fuel Type		x	x
Fuel Type*Gas Price			x
Adjusted R^2	0.749	0.904	0.887
n	749	565	339

The regression results from Table 3 are similar to those from Table 2 but the models are calibrated to data at higher level of detail as the data are additionally separated at the vehicle segment level in addition to the vehicle fuel technology and country. The models are the same with the exception of the inclusion of a dummy variable capturing the vehicle segment. One effect of this is a decrease in the impact of vehicle price on adoption down to 0.1% due to a $1,000 increase in price and is even insignificant in the full model (3). However, the effect of vehicle emissions and vehicle range is relatively close with the earlier results. The number of unique available models does increase substantially in importance: up to 3.3-4.8% increase per vehicle model on average.

Table 3: Regression results on *log(registrations)* with data divided by vehicle fuel technology and vehicle segment

Variable	(1)	(2)	(3)
Price ($)	-1.48e-6***	-1.00e-6**	-5.64e-7
	(3.73e-7)	(3.25e-7)	(1.78e-6)
Emissions Rate (g CO_2/km)	-0.013***	-0.009***	-0.012***
	(0.001)	(0.001)	(0.001)
Range (km)	0.007***	0.006***	0.004**
	(0.001)	(0.001)	(0.002)
Number of Models	0.048***	0.035***	0.033***
	(0.002)	(0.002)	(0.002)
Population	-	-	4.43e-10
			(1.12e-8)
GDP	-	-	2.47e-13
			(1.46e-13)
Unemployment	-	-	-0.063
			(0.075)
Fuel Type			
BEV (baseline)	0	0	0
	(0)	(0)	(0)

CNG	-0.903***	-6.101***	2.118
	(0.469)	(1.688)	(4.644)
Diesel	3.188***	1.383	10.719***
	(0.462)	(0.992)	(2.622)
Flexfuel	2.15***	4.389***	9.201***
	(0.505)	(1.068)	(2.769)
Hybrid	-5.856**	-5.7***	6.767**
	(2.016)	(1.688)	(2.663)
LPG	0.579	-0.351	9.3***
	(0.497)	(1.431)	(3.358)
PHEV	1.881***	1.86**	8.353**
	(0.286)	(0.598)	(3.576)
Petrol	3.734***	3.697***	13.197***
	(0.479)	(0.626)	(2.62)
Segment	x	x	x
Country	x	x	x
Country*Fuel Type		x	x
Fuel Type*Gas Price			x
Adjusted R^2	0.7	0.804	0.801
n	3,619	3,435	2,159

4.2 Preliminary model scenario projections

Here we display several vehicle adoption projection scenarios based on the three models of this project: a discrete choice consumer based model, a technology diffusion model, and a regression based on observed trends in the vehicle market and other country-level factors. The six countries represent a range of results across three scenarios (low, medium, and high) of price, EV model availability, and vehicle range. As these attributes improve for electric vehicles (lower prices, greater model availability, and higher range), we observe increasingly higher adoption across the new vehicle market. In Figure 7 we observe that the European countries have relatively high proportions of diesel vehicles whereas Chile and Japan consist initially of primarily gasoline vehicles. In the subset of results, the highest adoption of electric vehicles occurs in Portugal with a majority of BEVs and in Switzerland with a majority of PHEVs. In the "Low" adoption scenario, in Belgium total adoption is as low as 10% market share in certain countries by 2050 up to about 25% in the more aggressive "High" adoption scenario. Meanwhile, Switzerland has relatively high adoption at 75% market share even in the "Low" scenario and nearly a complete domination of the market in the "High" adoption scenario.

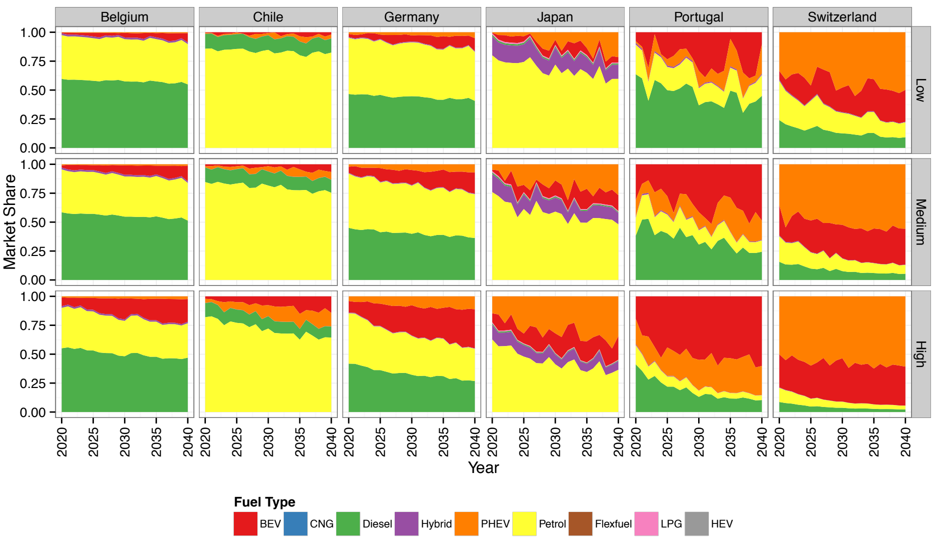

Figure 7: Scenario projection of vehicle sales by year broken down by fuel technology. The projections are based on the vehicle choice model results as described in Section 4.1.1. The Low, Medium, and High categories refer to scenarios of electric vehicle prices, model availability, and vehicle range as described in Section 3.4.

The Bass model projections of future electric vehicle adoption are shown for BEVs in Figure 8. As can be seen, the adoption curves can vary tremendously from country to country. Due to the uncertainty in the potential final market size of each of the technologies, we leave the results in terms of percentage of saturation. In the Bass projections, there is a stark difference in adoption potential between BEV and PHEV technologies. For example, BEVs in Canada saturate their market potential by around 2035 but PHEVs in Canada only reach 70% saturation by 2050. By far the fastest saturation occurs in China with extremely rapid growth in the market starting in 2018 and full saturation of new vehicle sales by 2025. However, many countries do not reach their market potential by 2050 including Australia, Chile, Japan, and Russia.

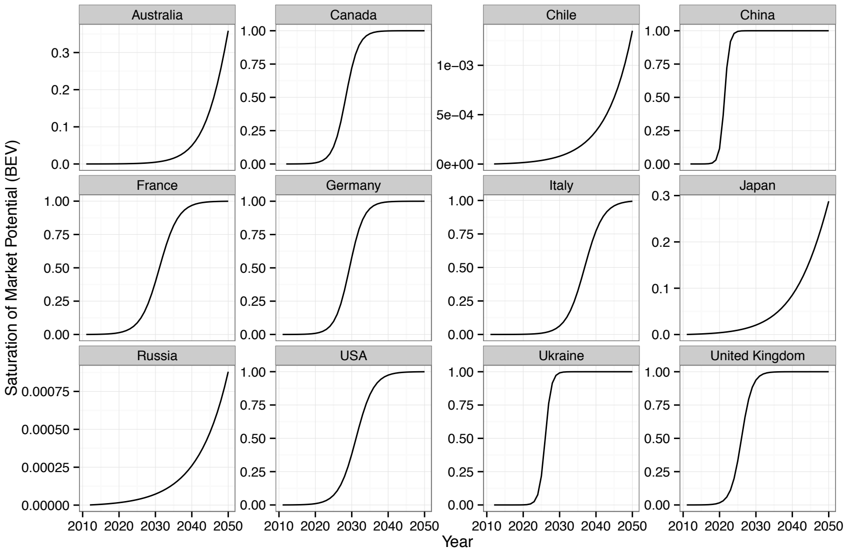

Figure 8: Bass model projections for battery electric vehicles, the projection scenario shows saturation of the market potential in different countries depending on their initial sales as seen in the data.

The projection generated from the regression model is relatively straightforward. The results are generated directly from the input assumptions and the corresponding vehicle attribute coefficients obtained from the estimation of the regression models. Under the most optimistic assumptions, annual sales of electric vehicles reach over 16 million by 2040 while the “Low” favorability scenario for EV adoption leads to a mere 4 million annual sales by 2040.

Lastly, we show a direct comparison of the electric vehicle projections from each of the three models in Figure 9. There is definite consistency in relative order of magnitudes between all the models though there are still stark differences in the rate of adoption. The Bass diffusion model has a very rapid initial growth due to the aggressive adoption of EVs in China but the sales level out by about 2025. Meanwhile, both the choice model and linear regression model grow continually in an exponential manner through 2040; though it should be noted that this growth pattern is an artifact of the modeling choice that the Bass diffusion model is able to explicitly integrate into its structure. Nevertheless, none of the models achieve a 100 million stock of EVs over the timeframe of the analysis with adoption ranging between 50 and 80 million EVs adopted by 2040.

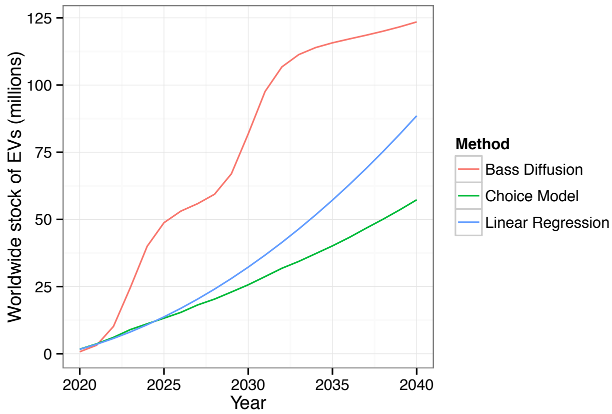

Figure 9: Model comparisons of three different projection methods: the discrete choice model, Bass diffusion of innovation model, and a linear regression model.

5 Discussion

5.1 Policy instruments

One of the critical implications of the multiple model projection conducted in this study is to investigate if these different approaches provide a consistent, robust basis on which to base policy decisions. The question of whether improving attributes and other aspects of favorability of electric vehicles leads to higher adoption of the technology is immediately apparent and consistent across all approaches. While the extent to which government agencies may wish to promote adoption of the technology may vary our research demonstrates that there is sufficient correlation between certain conditions and electric vehicle sales to point toward increased sales in the future if certain policy levers are implemented. From a vehicle price perspective, many government institutions already provide incentives based subsidies though their size and longevity can have a definite impact on adoption in the future. Vehicle driving range is an important attribute that has had a natural progression in the technology of increasing though certain policies such as the California Zero Emission Mandate's recent update of the credit system has proven to directly target this attribute as well.

These models do not align completely; the Bass diffusion curves achieve much faster, steeper initial penetration of EVs than the other two approaches and may reflect an inherent tendency in this method to define a market penetration pathway, with the steepness and saturation point the main variables. The decision choice and regression approaches, when used to project, do not necessarily achieve any increased future market shares. These both show relatively slow initial increases given the trajectories we set for explanatory variables, though eventually catch up to the Bass curve.

The overall takeaway is that it may be quite challenging to achieve targets such as 100 million electric vehicles worldwide by 2030 (the IEA and UN targets), though there could be changes in markets as well as consumer behavior that are poorly captured in these models. As always with projecting into the future with past data, the conditions prevailing (such as awareness and attitudes about EVs) are implicitly assumed to continue into the future. Tesla has shown that such perceptions can change rapidly, and the entry into the market of additional higher range battery-electric vehicles during the next two years will provide a fresh perspective on how consumers react to higher range.

5.2 Future work with the current data sets and models

There are several notable issues in our modeling efforts that need to be improved upon, and our work in this area, and with this data, will continue. In general there are issues with the data including some possible errors that may influence the model calibration and results. Due to the large size of the dataset, identifying edge case errors is inherently difficult and will require additional time and effort by team members to clean. There are also additional explanatory variables that we would like to introduce such as the presence of recharging infrastructure in different countries. The issue there is that at a national level, recharging infrastructure is averaged over many areas with dense infrastructure and many without, and this may provide a poor correlation with the sales of vehicles within a country. But we hope to test its significance upon completion of data development in this area.

In the choice modeling, the erroneous coefficients among approximately 20% of the modeled countries need to be re-run. There are several approaches we intend to take including a multi-year model (rather than calibrating the choice model only to 2015 sales). Additionally, we are taking a different approach to the alternative-specific constant estimation that may prove to have more reliable estimation and convergence when solving the model.

In the diffusion model, we intend to expand our modeling efforts from the Bass model in order to incorporate other exogenous variables such as price, knowledge/awareness, and infrastructure. The Generalized Bass Model is a step towards increasing modeling complexity but there are a number of other diffusion models in the literature, which can be leveraged to further investigate the adoption of electric vehicle technology.

For the regression model, some nuance can be given by providing uncertainty through bootstrapping results based on the standard errors of the results. In addition to possible changes from simply cleaning the data, additional model specifications can be investigated as well as different structural assumptions including non-linear additive models.

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