Rhodium Group

Projecting Vehicle Sales

A Review of Light-Duty Vehicle Adoption Models

March 24, 2023

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CHAPTER 1

The Importance of Decarbonizing Light-Duty Vehicles

To meet its nationally determined contribution under the Paris Agreement, the US must reduce greenhouse gas (GHG) emissions by 50-52% below 2005 levels by 2030. Achieving this ambitious goal will require a concerted effort across all levels of government and in all sectors of the economy (Larsen, et al., 2021). Furthermore, this interim target only gets the country halfway toward its goal of net-zero greenhouse gas emissions by 2050 (Department of State and Executive Office of the President, 2021).

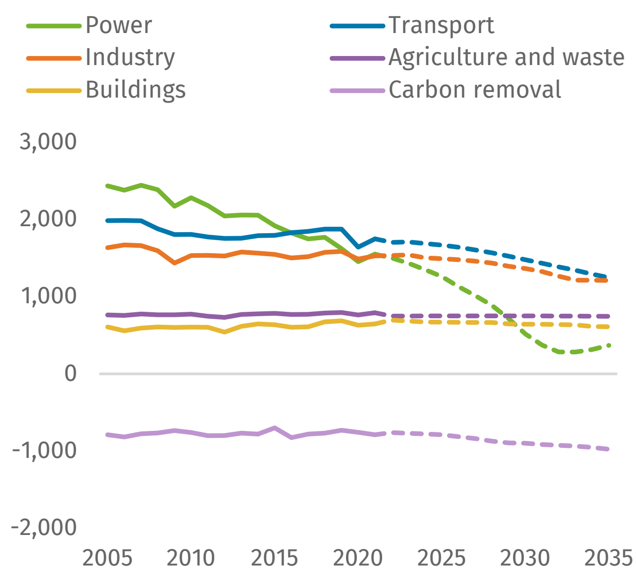
Though the power sector had historically been the largest GHG emitter, since 2016, the transportation sector has claimed that title (Figure 1). Moreover, while the Inflation Reduction Act (IRA) is projected to decrease economywide GHG emissions to 32-42% below 2005 levels, much of that reduction comes in continued gains in the power sector rather than substantial reductions in other parts of the economy (Larsen, et al., 2022). While we project power sector emissions fall to 69-79% below 2005 levels, transportation emissions only drop to 18-26% below 2005 levels. Further, even with the incentives provided in the IRA, we expect the transportation sector to remain the highest-emitting sector through 2035. Put another way, there are plenty of emissions left to cut in the transportation sector, and additional policy action will be necessary to drive down transportation sector emissions and keep the US on its decarbonization pathway through 2030 and beyond.

The transportation sector is diverse in its energy use and sources of emissions, but the largest share—more than half—comes from the combustion of liquid fuels in light-duty vehicles (LDV) (Figure 2). Though reductions will be required across the board in a net-zero transportation sector, commercial technologies (like electric vehicles and other zero-emitting vehicles, or ZEVs) are most widely available today to reduce emissions from LDVs, making them a promising place to work on driving further emissions reductions.

FIGURE 1

Historical and projected US GHG emissions

Million metric tons of CO_2-equivalent, projections in dashed lines



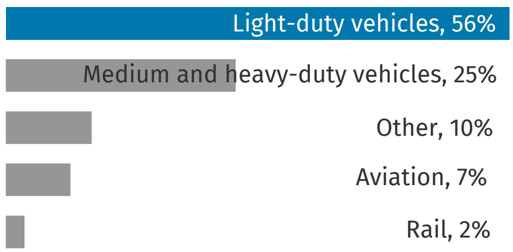
Source: Rhodium Group. Projections reflect central emissions scenario from Larsen, et al., 2022.

Progress is already underway on this front. The Energy Information Administration (EIA) reported that electric vehicle sales represented nearly 5% of total LDV sales in the fourth quarter of 2021, up from less than 1% just a few years prior (Dwyer, 2022). But the LDV fleet faces a stock turnover problem: in any given year, only a small percentage of LDVs on the road are new, such that even if 100% of LDV sales are ZEVs starting in 2030, the fleet wouldn't be fully ZEV until after 2040 (Larsen, King, Kolus, & Wimberger, 2021). Every vehicle sale today matters, given how long it will be on the road.

FIGURE 2

US transportation emissions by source in 2021

Percentage of total transportation sector CO_2e emissions



Source: Rhodium Group. Note: Other includes emissions from mobile combustion, pipelines, and HFCs from mobile A/C.

Given this context, it is critically important to understand consumer adoption of zero-emitting LDVs to inform policy design to further this goal. Of course, the price of owning and operating a vehicle is a critical factor in a consumer's vehicle purchasing choice. But, depending on the analysis, cost parity between some ZEVs and their conventional internal combustion engine (ICE) counterparts is either fast approaching or has already been achieved (Lutsey & Nicholas, 2019; Harto, 2020; Orvis, 2022). Since ZEV sales shares are still low relative to incumbent ICE vehicles, further explanation is necessary to understand what drives this outcome. Numerous methodological approaches have been developed and deployed in a wide range of consumer adoption models that seek to inform this understanding further.

This study seeks to inform policymakers and the modeling community by reviewing the range of consumer adoption modeling approaches used in projecting future ZEV sales. The study first reviews three main categories of consumer adoption techniques—market diffusion models, consumer choice models, and agent-based models—and explains their basic function and the strengths and weaknesses of each approach. We then dive deeper into specific consumer choice models used in policy-relevant modeling contexts. Finally, we offer some concluding thoughts.

CHAPTER 2

Models for Projecting LDV Adoption

As hybrids, electric vehicles, and a range of other alternative fuel LDVs and ZEVs have emerged into the auto marketplace, a rich literature of technology adoption modeling has developed to forecast their future sales. This work often extends techniques developed in different fields to explain the factors behind LDV adoption and project future technology adoption trends. In this chapter, we provide a brief overview of the three most popular models used for LDV market forecasts: market diffusion models, consumer choice models, and agent-based models.

Market diffusion models

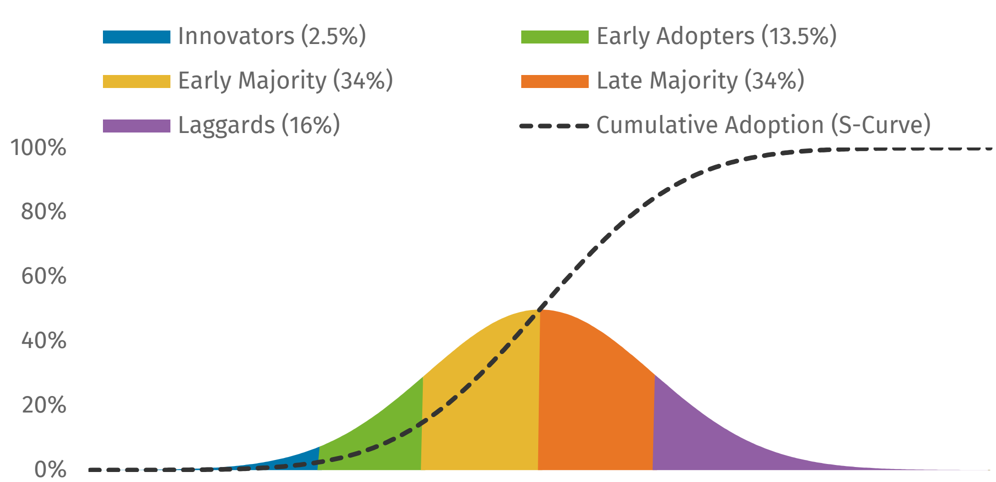
Market diffusion models are used to forecast the adoption patterns of new technologies over time. They were first introduced in the marketing discipline in 1969 with the publication of the Bass new product diffusion model. The mathematical model captures new product life-cycle dynamics and serves as a decision aid for product launch decisions (Mahajan, Muller, & Bass, 1990). Since then, they have been applied in various markets, including energy, transportation, and telecommunications (Al-Alawi & Bradley, 2013).

Diffusion models are grounded in the diffusion of innovation theory, which describes the rate of an innovation's adoption as an S-shaped curve and seeks to explain the rate of new product diffusion in the market (Shogren, 2013). Several internal and external factors, which may or may not be controllable, influence new product adoption (Mansfield, 1961). In LDV adoption, the amount of media advertising done to promote the new vehicle technology is an example of an external factor, while free marketing about the new vehicle technology triggered by the experiences of early adopters is an example of an internal factor. Other examples of relevant external factors may include government support and the availability of supporting infrastructure (e.g., charging stations). Other internal

FIGURE 3

S-shaped adoption curve and stages of adoption

Cumulative adoption percent (dashed line); percent of market comprised of a given stage (distribution)



Source: Rhodium Group, based on Briscoe, Trewhitt, and Hutto (2011) factors may include vehicle price and usability (Zhu & Du, 2018).

Everett Rogers, the originator of diffusion of innovation theory, suggested that these factors of influence include the innovation itself, adopters, communication channels, time, and social systems (Rogers, 1995)

The diffusion of innovation theory is typically modeled as a bell-shaped, normal distribution reflecting the shares of adopter types at different stages in a product's life cycle. The distribution is broken up into five main categories of adopters: innovators, early adopters, early majority, late majority, and laggards, as demonstrated in Figure 3 (Rogers, 1995).

The three most common diffusion models used for the automotive market are the Bass, Gompertz, and Logistic models (Al-Alawi & Bradley, 2013). All three models describe an S-shaped cumulative adoption curve—however, they differ in terms of their functional form and the rates at which asymptotic limits are reached.

The Bass formulation is defined as:

$$Y(t) = M * \frac{1-e^{-(p+q)t}}{1+\frac{q}{p}*e^{-(p+q)t}} \qquad (2.1)$$

where Y is the total number of adopters at time t; M is the market potential or ultimate number of adopters; p is the coefficient of innovation; and q is the coefficient of imitation (Sudtasan & Mitomo, 2017; Al-Alawi & Bradley, 2013). The coefficients of innovation and imitation reflect external and internal influences on rates of product adoption, respectively.

The Logistic model formulation is defined as:

$$Y(t) = \frac{M}{1+ e^{-a(1-b)}} \qquad (2.2)$$

where M is the market potential, a describes the speed at which adoption occurs, and b denotes the inflection point at which 50% market potential is reached (Sudtasan & Mitomo, 2017; Al-Alawi & Bradley, 2013).

Lastly, the Gompertz model formulation is similar to the Logistic formulation:

$$Y(t) = M * e^{-e^{-a(t-b)}} \qquad (2.3)$$

where M is the market potential, a describes the speed at which adoption occurs, and b denotes the inflection point at which 36.8% of market potential is reached (Sudtasan & Mitomo, 2017; Al-Alawi & Bradley, 2013).

Most of the parameters of these diffusion models can be estimated using regression analysis and historical sales data for the new vehicle technology of interest. When sales data does not exist because the technology has not yet reached the marketplace, adoption parameters can be derived from survey inferences or from analog technologies believed to exhibit similar market behavior (Al-Alawi & Bradley, 2013). In addition to this historical data, diffusion models require exogenous estimates of the long-run ultimate market potential and the period in which peak sales occur (Al-Alawi & Bradley, 2013). Once the models have been estimated, they can be used to predict cumulative adoption levels for new vehicle technologies over time.

Another common assumption underlying all three models is the notion of product generation—that vehicle technologies are periodically redesigned or updated and sold in successive generations (Al-Alawi & Bradley, 2013). The length of time between successive generations will often differ from one technology to another.

The Bass model has been used to forecast the adoption of new technologies based on interactions between adopters and potential adopters (Bass, 1969). It is applied under the assumption that no competing technology exists in the market. Adopters reflected in the model are identified as either innovators or imitators. Innovators are the early adopters of a new technology that do so in response to a "mass-media" effect. In contrast, imitators are those that adopt in response to a "word-of-mouth" or "social contagion" effect (Al-Alawi & Bradley, 2013). The conceptual underpinnings of the model are that the degrees of innovation and imitation drive the speed and timing of adoption.

The Bass model has been extended to a generalized Bass model, a formulation that adds one or more explanatory variables to improve the model's predictive power (Kinter-Meyer, et al., 2022). In ZEV adoption modeling, these additional variables have included vehicle price and the value of fuel saved (McManus & Senter Jr., 2009).

In addition to the Bass model, the Gompertz form has also been used in LDV market projections, and Logistic models have proven to be useful in applications where the new technology is assumed to be replacing some existing technology because it is more economically and technically efficient to do so (Ayyadi & Maaroufi, 2018; Lamberson, 2009).

Research applications

Examples of studies applying diffusion models in the automotive market include a 2009 study by McManus and Senter (2009) in which a range of models are used to forecast adoption patterns of plug-in hybrid electric vehicles (PHEVs) in the U.S. The authors projected that PHEV sales would reach a maximum of 350,000 after seven to eight years. In a later study focusing on a non-U.S. market, Ayyadi and Maaroufi (2018) predicted the diffusion of electric vehicles (EVs) in the Moroccan automotive market using the Bass, Gompertz, and Logistics models. Of the three models, they discovered that the Bass model fit their data the best. EV sales in the market were predicted to peak after 14 years, depending on government subsidies.

Outside the academic literature, Bloomberg New Energy Finance (2022) uses a generalized Bass diffusion model, informed by a complementary total cost of ownership calculation, to project electric vehicle sales in its annual Electric Vehicle Outlook—a very commonly cited source of EV adoption projections. In addition, the International Energy Agency's (2022) World Energy Outlook uses a Gompertz diffusion model to project total vehicle stock.

Advantages and disadvantages

Diffusion models have proven to be popular for predicting demand for new vehicle technologies. Much of this is due to their ease of implementation and how easily they can be estimated using historical data for the new technology itself or analogs with similar adoption characteristics.

Diffusion models are also generally recognized as appropriate for use in "pre-production" and very early-stage technologies (Becker & Sidhu, 2009). In particular, the inclusion of a parameter that incorporates network effects—the impacts of interactions between adopters and potential adopters—helps this formulation reflect a product increasing its market share non-linearly over time and based on others' adoption behaviors (McManus & Senter Jr., 2009).

One major disadvantage of diffusion models is that the total market size and period of peak sales must be exogenously estimated before the model can be developed (Wu & Trappey, 2008). Incorrectly estimating either of these parameters can yield different market outcomes with commensurately different emissions implications. In addition, diffusion models assume technologies diffuse within a market with no competitor technologies. Of course, this is not the case for the broader LDV market, so it is critical to define the market appropriately when projecting a given technology's uptake.

Consumer choice models

Consumer choice models are statistical models used to predict choices made by individuals or groups. Their applications span social sciences, marketing research, transportation, and medicine. The logit model is the most heavily used choice model in the vehicle adoption literature. Logit models estimate the probabilistic preferences of consumers. More specifically, they theoretically or empirically model choices made by individuals from a finite set of alternatives (Train, 2009). Consumer choice models like the logit operate within a framework of rational choice. They are grounded in consumer utility theory, which states that given a finite set of options or choices ("choice set"), an individual will choose the option that maximizes their utility or well-being (Train, 2009).

Consumer choice models are built on statistical relationships that relate an individual's choice to the attributes of both the decisionmaker and the set of alternatives (Ying & Kuhfeld, 1995). In the context of the auto market, the type of vehicle chosen by a person is statistically influenced by personal characteristics like income and age, as well as attributes of the vehicle such as price, fuel efficiency, and ownership costs.

Empirically estimating a choice model is a two-stage process. The first stage is generating a choice set of technologies available to each decisionmaker. Next, a utility model is fitted with consumer utility as the dependent variable and the characteristics of the buyers, characteristics of the choices, and an error term as explanatory variables. In modeling LDV choice, historical sales data is often used in conjunction with historical attributes of the choice set and buyer characteristics (Al-Alawi & Bradley, 2013). Once the final choice model is estimated, it can be used in conjunction with expectations of future buyer characteristics and vehicle attributes to forecast the relative market shares of each vehicle technology option over time.

Historical data on vehicle attributes are sometimes limited or do not exist for new advanced technologies like EVs. Common workarounds include using survey inferences or alternative stated preference methods to derive sensitivities of choice to vehicle attributes (Cao, 2006). However, relying on stated preference rather than revealed preference can introduce bias to the estimation as consumers may behave differently when faced with a purchase decision rather than responding to a survey (Liao, Molin, & van Wee, 2017). Attributes often incorporated into these models include price and other ownership costs, fuel efficiency, refueling/charging infrastructure availability, driving range, range anxiety, and frequency of battery replacement (Santini & Vyas, 2005). We review several consumer choice models and detail their explanatory variables in the next chapter.

Multinomial logit (MNL) and nested multinomial logit (NMNL) models are two commonly used types of consumer choice models to evaluate vehicle purchases (Al-Alawi & Bradley, 2013). Both models are rooted in consumer utility theory, where an individual consumer chooses an alternative from a set of alternatives to maximize their utility (Train & Winston, 2007). This dynamic is depicted in Equation (2.4), where the probability ($P_{i,n}$) that the *nth* individual will select the *ith* alternative from a set C containing all possible alternatives j is specified as:

$$P_{i,n} = P(U_{i,n} \geq U_{j,n}, \forall j \in C_n, j \neq i) \qquad (2.4)$$

The basic multinomial logit model is described as:

$$P_{i,n} = \frac{e^{U_{i,n}}}{\sum_{j \in C_n} e^{U_{j,n}}} \qquad (2.5)$$

where:

$$\sum_{i \in C_n} P_{i,n} = 1 \qquad (2.6)$$

The above utility equation for the *nth* consumer choosing the *ith* alternative ($U_{i,n}$) is defined as:

$$U_i = \sum_n \beta_n X_{i,n} + \varepsilon_i \qquad (2.7)$$

$X_{i,n}$ is an explanatory variable for the *nth* individual and the *ith* alternative. β_n is the regression coefficient for $X_{i,n}$capturing the relative change in utility given an incremental change in the explanatory variable. ε_i is the random component for the *ith* alternative.

Greene, Duleep, and McManus (2004) extend the basic multinomial logit approach to allow for model estimation with inference for the values of vehicle attributes. Their generalized cost coefficient approach describes an individual's utility function associated with choosing a vehicle as a weighted sum of relevant attributes (e.g., price, reliability, efficiency). A random component is added to the utility function to capture unquantified yet relevant attributes. The utility function is defined as:

$$u_{ij} = b(A_i + \sum_{l=1}^{K} w_l x_{i,l} + \varepsilon_{i,j}) \qquad (2.8)$$

where u_{ij} is the utility ranking score for the *ith* vehicle for the *jth* individual; b is a parameter determining the sensitivity of an individuals' choices to changes in the dollar values of the alternatives; A_i is a constant term that denotes the dollar value of attributes of vehicle i not included in the set of quantified attributes; w_l is the weight of the *lth* attribute $x_{i,l}$; and $\varepsilon_{i,j}$ is the *jth* individual's random component for the *ith* vehicle make and model (Al-Alawi & Bradley, 2013).

The conditional probability that the *jth* individual will choose the *ith* vehicle make and model given the *kth* vehicle class is defined by the MNL function:

$$p_{i|k} = \frac{e^{bu_i}}{\sum_{l=1}^{L} e^{bu_i}} \qquad (2.9)$$

The probability $p_{i|k}$ serves as an indicator of the *ith* vehicle's market share given that the population of buyers is large enough (Greene, Duleep, & McManus, 2004).

As in Greene, Duleep, and McManus (2004), in cases where the vehicle choice set can be deconstructed into subsets or "nests", a NMNL model is used to estimate the probability of an individual selecting a particular vehicle type based on a nested decision-making process. The nested decision involves the individual buyer first selecting a vehicle class, then selecting a vehicle make and model from within that class. The utility function for each *kth* vehicle class is a probability-weighted average of the utility scores of vehicles within the class. The expected utility function for the *kth* vehicle class is defined as:

$$U_k = \frac{1}{b} \ln \left(\sum_{i=1}^{n_k} \exp\left(u_{l,k}\right)\right) \qquad (2.10)$$

The probability that an individual buyer will select a vehicle from the *kth* vehicle class is:

$$p_k = \frac{\exp\left(A_k + BU_{k,i}\right)}{\sum_{K=1}^{n} \exp\left(A_K + BU_{K,i}\right)} \qquad (2.11)$$

In the above equation, K is the summation of all vehicle classes and n is the number of classes. Like A_i, A_k is a class-specific constant term representing the dollar value of unquantified attributes of the *kth* vehicle class. Similarly, B is analogous to the parameter b, serving as a slope parameter measuring the sensitivity of class choices to changes in their expected values.

The probability that the *ith* vehicle type will be selected from the *kth* vehicle class is the product of Equations (2.5) and (2.9).

$$p_{ik} = p_{i|k} * p_k \qquad (2.12)$$

The decision to use either an MNL or NMNL model largely depends on the assumptions about how consumers make decisions and the existence of correlation between alternatives (Train, 2009). A property of MNL models is the independence of irrelevant alternatives, which holds that the ratio of probabilities of choosing one alternative over another is unaffected by the addition (or removal) of another alternative (EPA, 2012). This assumption is generally violated in LDV choice modeling (and other cases); NMNL relaxes this assumption by grouping alternatives into nests (Liao, Molin, & van Wee, 2017). Both MNL and NMNL models assume homogenous distribution of consumer tastes (within nests, in the case of NMNL).

To address this limitation, scholars and practitioners began using mixed logit (ML) models, allowing for heterogeneous consumer tastes, which became common in the literature beginning around 2010 (Liao, Molin, & van Wee, 2017). ML models estimate consumer utility using observed characteristics but also allowing for random variation unrelated to observed characteristics.

Train and Winston (2007) estimate a ML consumer choice model with the following utility function for consumer n and vehicle j:

$$U_{nj} = \delta_j + \beta' x_{nj} + \mu'_n w_{nj} + \varepsilon_{nj} \qquad (2.13)$$

where δ_j is the average utility derived by all consumers from vehicle j; x_{nj} is a set of consumer characteristics interacted with vehicle attributes, with β' representing the population-mean coefficient for each factor; and w_{nj} is a set of vehicle attributes interacted with consumer characteristics for which tastes vary, with μ'_n representing a vector of random terms. Finally, ε_{nj} captures all remaining elements of utility and is assumed to be independent and identically distributed. The probability of consumer n choosing vehicle i from the suite of j vehicle options can be calculated via mixed logit model:

$$P_{nj} = \int \frac{e^{\delta_i + \beta' x_{ni} + \mu' w_{ni}}}{\sum_j e^{\delta_j + \beta' x_{nj} + \mu' w_{nj}}} \tag{2.14}$$

EPA (2012) notes the increased complexity of a ML model relative to MNL and NMNL, highlighting that additional information and simulations are required, but calls the ML formulation "still quite feasible."

Research applications

Consumer choice models are a popular tool for understanding adoption patterns for new vehicle technologies. We provide more detail on several specific model applications relevant to policy conversations in Chapter 3. In an example from the academic literature, Bandivadekar (2008) used a discrete choice modeling approach to estimate the market penetration rate of advanced LDV technologies. Results from four modeling scenarios estimate new hybrid electric vehicle (HEV) sales ranges between 15% and 40% by 2035. In the case of new PHEVs, sales are estimated to range between 0% and 15% by 2035.

Al-Alawi and Bradley (2013) catalog a range of other examples of uses of consumer choice modeling for LDVs, both in the US and internationally. In addition to this list, the International Energy Agency (2022) uses a logit function to project future sales shares of ICE vehicles, hybrids, EVs, and other competing technologies grounded in current and future technology costs.

Advantages and disadvantages

An important advantage of consumer choice models is their ability to represent individual decision-making as part of a market segment. They are also less complex, more transparent, and easier to implement than other modeling constructs, such as agent-based models. Another advantage to consumer choice models is their ability to consider competing technologies in the choice set.

Because choice models exploit a validated relationship between vehicle choice and the characteristics of the buyers and the vehicle attributes, they are useful for analyzing how major real-world factors (e.g., technological changes, policy) can affect the sales evolution of new, advanced vehicle technologies over time.

A significant disadvantage of choice models is that rich historical data is needed to calibrate the model—however, data for newer vehicle technologies is often lacking or does not exist. In these cases, practitioners often look to survey data or their own hypotheses to draw inferences on consumer preference sensitivities, which may be less reliable. Parameters may also be able to be sourced from other papers.

These models are also sensitive to the inclusion and values of explanatory variables used to estimate the model; using faulty, incomplete, or outdated assumptions can yield flawed estimates. Dormeus et. al. (2019) compare the accuracy of a NMNL model with a simple forecast based on persistent market shares and find that the simpler model outperforms the NMNL because changes in vehicle price are linked to unobserved changes in other aspects of a vehicle's quality.

Care must also be taken not to generalize the behavior of early adopters to the entire market, which can be an inherent function of fitting the model to historical data. Choice models may also encounter issues with overfitting (Liao, Molin, & van Wee, 2017).

Consumer choice models also do not directly estimate the absolute size of a vehicle market but rather characterize the evolution of vehicle sales shares over time (Podkaminer, Xie, & Lin, 2017).

Agent-based models

An agent-based model (ABM) is a bottom-up, stochastic computer simulation model used to understand complex systems by capturing the actions and interactions between individual agents operating within the system to observe the emergence of coherent and dynamic system behaviors (Gilbert, 2019; Zhang, Gensler, & Garcia, 2011). Agents (i.e., individuals or entities) are inherently designed to have control over how they interact with other agents within the simulation environment. ABMs have proven useful for understanding intricate relationships and potential causal mechanisms driving system behavior (Gilbert, 2019). They have been applied in many fields of study, including vehicle technology adoption, biology, epidemiology, economics, and population dynamics.

In ABMs, agent interactions with other agents and the environment are based on decision rules and information available to each agent. Decision rules describe: (1) how the simulation environment acts on its own; (2) how agents behave on their own; (3) how agents interact with one another; and (4) how agents interact with the environment (DeAngelis & Diaz, 2019). Typically defined at the agent level, decision rules are characterized using mathematical equations/algorithms and describe agent actions at temporal scales (Stephens T. , 2010). ABM simulations repeatedly execute the rules that define them. Through this iterative process, the combined behaviors of the agent can be measured gradually and reinjected into the behavior of the same agents (Manzo & Matthews, 2014).

ABMs have proven helpful in capturing systems of heterogenous agents exhibiting distinctive behaviors. Within the context of forecasting, their use to observe the penetration of new vehicle technologies has depicted different types of agents within the simulation environment (Sullivan, Salmeen, & Simon, 2009; Cui, Liu, Kim, Kao, & Tuttle, 2011; Eppstein, Grover, Marshall, & Rizzo, 2011). Although the number and type of agents can vary, typical agents depicted include consumers, automakers, fuel suppliers, and policymakers (Al-Alawi & Bradley, 2013). The consumer agents are characterized by their preferences and demographics and represent vehicle demand. Automaker agents are responsible for supplying vehicle technologies, with vehicles being characterized by vehicle class, fuel type, performance, costs, etc. Fuel supplier agents are responsible for providing fuel resources. Their actions are primarily dictated by consumer responses to policies (e.g., gas tax increases) or standards (e.g., clean fuel standards) that affect fuel use. Policymaker agents are responsible for implementing policies and standards impacting vehicle sales and use.

Each agent in an ABM is described by a series of attributes influencing their decisions. Characterizing these attributes requires using relevant external data sources combined with modeler intuition, behind which values will likely bring about plausible agent behavior. For example, in the context of vehicle adoption, the attributes of a consumer agent might include average trip distance and travel speeds. Distributions for these attributes can be derived using National Household Travel Survey data (Stephens T. , 2010). For the most part, the data needs and corresponding sources will largely depend on the system the ABM is simulating and its represented agents. Like many models, the degree of realism depicted in an ABM simulation depends on the quality of data used. Accurate, reliable data is needed for parameterizing agents if ABMs are to be used for policy analysis (An, et al., 2021).

Research applications

ABMs have been used in the academic literature to forecast market penetration of new advanced vehicle technologies such as HEVs, PHEVs, and EVs. For example, Sullivan et al. (2009) used an ABM to evaluate the penetration of PHEVs into the US auto marketplace under various consumer, economic, and policy conditions. The model included four classes of agents: consumers, government, fuel suppliers, and automakers. Their agent-based modeling study revealed that tax rebates, PHEV subsidies, and sales tax exemptions had the most impact on PHEV market penetration.

In a later study, Noori and Tatari (2016) developed, verified, validated, and applied a four-agent ABM to predict future market shares of electric vehicles and ICEVs in the US in 2030 under different scenarios. Modeling results indicated that government subsidies play an important role in the market penetration of EVs. When combined with a "word-of-mouth" effect, the authors projected that EVs could comprise up to 30% of new vehicle sales, on average, in 2030.

Advantages and disadvantages

A significant advantage of ABMs is their flexibility across multiple dimensions. For example, agents can be easily added to or subtracted from the model. Another example is how easy it is to modify the relative complexity of modeled agents. In modeling vehicle purchase decisions, ABMs consider different market intricacies (e.g., household budget limitations) that can influence individual purchase decisions. Another important advantage is their ability to include social processes and other non-monetary influences on the decision-making of system agents, including exogenous shocks like sudden changes in government regulations or a sharp decrease in fuel supply (Sullivan, Salmeen, & Simon, 2009). ABMs can also represent hypothetical consumer behavior, depending on how its agent rules are designed, unlinking results from historical data (Noori & Tatari, 2016).

The biggest disadvantage facing ABMs is that they can be quite complex. There are typically issues with computational efficiency, given that most ABMs are operated on personal computers. ABMs are also challenging to develop, test, parameterize, and validate. Simulating the dynamics of a large population (like car buyers in the US) may result in ABMs becoming "unwieldy" (Bruch & Atwell, 2015).

Another facet of the complexity in developing ABMs is that each actor's behavior must be specified. Developers must ensure that fundamental assumptions of the model are consistent with basic physical and economic principles; expanding the model too quickly may result in indefensible assumptions that inadvertently run afoul of "real world" dynamics (Wallace, Geller, & Ogawa, 2015)

CHAPTER 3

Consumer Choice Applications in Policy-relevant Models

The broad categories of models discussed in the previous chapter each have their advantages and disadvantages. Some are more suitable than others for specific analytical tasks, depending on the overall research objective and scope and data availability. Many of the most policy-relevant models used to forecast sales of advanced vehicle technologies adopt a consumer choice modeling framework. As discussed in Chapter 2, consumer choice models have proven to be useful for analyzing how major, real-world factors (e.g., technology, infrastructure, consumer behavior, policy) can affect the sales of new vehicle technologies over time.

In this chapter, we provide details on the characteristics and features of a subset of consumer choice models, homing in on those developed by federal agencies or federally funded research institutions. For comparison, we also discuss a transport sector model for the European Union (EU). In this chapter, we build on and update a comparison of vehicle choice models published by Argonne National Laboratory (Stephens, et al., 2017).

We note the policy applications in the discussion of each model, but in general, the models in this chapter are used in regulatory settings (e.g., EPA's OMEGA model, the state of California's use of LAVE-Trans and ADOPT, the EC's PRIMES-TREMOVE), in legislative discussions and to establish commonly cited baselines (e.g., NEMS), or to guide the work of federal agencies (e.g., MA3T).

This is not an exhaustive review of all policy-relevant consumer choice models. Some models, like the Center for Sustainable Energy's Caret model, have been influential in legislative conversations but lack publicly available documentation. Other models lack full-scale consumer choice components, like Evolved Energy Research's EnergyPATHWAYS model (the energy system model powering Princeton University Zero Lab's Rapid Energy Policy Evaluation and Analysis Toolkit). Still another set of models also exist in the academic literature that have not been applied in a policymaking setting.

NEMS

The **National Energy Modeling System (NEMS)** is developed and maintained by EIA. EIA (2022) uses NEMS to produce its benchmark Annual Energy Outlook (AEO), an assessment of the US energy system under current policy through 2050. The AEO is one of the most cited data sources for understanding the evolution of the US energy system. Rhodium Group and other organizations use their own versions of NEMS to produce tailored policy analyses (King, et al., 2022; Clemmer, 2016). NEMS is updated annually as part of the AEO development cycle.

The NEMS Transportation Demand Module (TDM) provides projections of transportation energy demand via four submodules—LDV, air travel, freight transport, and miscellaneous energy demand. In the LDV submodule, the consumer vehicle choice component (CVCC) is used to estimate the market penetration of conventional and 14 alternative fuel vehicles, taking as its starting point projections of total new vehicle sales generated in a separate macroeconomic module. It uses a nested multinomial logit choice function to calculate the market shares.

The nested tree structure of the logit has two main stages. The first stage determines sales shares for five vehicle groups: conventional (e.g., gasoline, diesel, etc.), hybrid, dedicated alternative fuel (e.g., dedicated compressed and liquified natural gas), fuel cell, and EVs, while the second stage determines sales shares for more granular vehicle classes within each of these groups. A third stage estimates the proportion of travel in which flex or bi-fuel vehicles use alternative or gasoline fuel.

The CVCC calculates vehicle utility using a set of vehicle attributes, including vehicle price (as modified by the separate Manufacturer Technology Choice Component in which manufacturers respond to federal fuel economy policy), fuel cost, vehicle range, fuel availability, battery replacement cost, vehicle performance, home refueling capability, maintenance costs, luggage space and make and model availability. The coefficients applied to these attributes in the NMNL formulation remain constant over time as applied by EIA, though the user can set the model to vary these coefficients over time. In addition to these vehicle attributes, the NMNL includes an intercept term representing the utility consumers assign to the vehicle not otherwise captured in the vehicle attributes. EIA updates the intercept term to align the first model projection year with historical sales data. In addition to modeling the impact of federal fuel economy policy (i.e., Corporate Average Fuel Economy standards), the TDM can evaluate various other policies, including fuel taxes, vehicle subsidies, ZEV mandates, and other policies related to transportation energy use and GHG emissions. For additional information on the NEMS TDM, refer to EIA (2022).

OMEGA

The Environmental Protection Agency (EPA) has regulated greenhouse gas emissions from LDVs since model year (MY) 2012, after the Agency's endangerment finding (EPA, 2010). EPA created the **Optimization Model for Reducing Emissions of Greenhouse Gases from Automobiles (OMEGA)** to estimate the benefits and costs of meeting user-specified GHG emission targets through different technology packages applied to vehicles to support the development and promulgation of its first LDV GHG standards. EPA continued use of OMEGA in its LDV GHG standards for MY2017 and later, as well as its initial final determination in its midterm evaluation for My2022-2025 (EPA and NHTSA, 2012; EPA, 2017). EPA subsequently used an alternative tool, the National Highway Traffic Safety Administration's (NHTSA) CAFE Compliance and Effects Modeling System (also commonly called the Volpe model), to model the effects of the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for MY 2021–2026 as well as its recent revised standards for MY 2023 and later (EPA and NHTSA, 2020; EPA, 2021)

The initial version of OMEGA is an accounting model, not an economic simulation model that would allow vehicle sales to interact with changes to vehicle cost and performance.[1] EPA has been developing a new version of the model, OMEGA version 2.0, to address this issue by including a new Consumer Module responsible for predicting changes in the LDV vehicle sales or sales shares over time given policy-induced changes in vehicle characteristics such as new vehicle price, fuel operating costs, and other important attributes. The final version of OMEGA v2.0 was not available at the time of drafting, so this review is based on the publicly available demonstration version.

This new consumer module adopts a modified logit estimation approach based on a similar method used in the Global Change Analysis Model (GCAM) developed and maintained by the Joint Global Change Research Institute (JCGRI). The model estimates sales shares of competing vehicle technologies as a function of the generalized cost of the technology while accounting for the speed of its public acceptance. Model users define the different vehicle market classes for which the sales shares are estimated as well as two important parameters for each technology: a share weight, which calibrates sales shares to historical values and establishes how quickly consumers accept a new technology, and a price sensitivity parameter to set consumer responsiveness to price (Joint Global Change

[1] The Volpe model also lacks a full-scale consumer choice component. EPA developed a consumer choice model for the original version of OMEGA, but it was never used in a regulatory setting (EPA, 2012)

Research Institute, n.d.). Vehicle ownership costs can be further informed by manufacturer decisions to implement new technologies in the producer module of OMEGA, which models how LDV manufacturers respond to regulatory policy by altering vehicle attributes. JCGRI describes as an advantage of the modified logit formulation of the consumer choice model the fact that it can take a long time for uncompetitive technologies to be pushed out of the market, which is potentially representative of an adoption pathway for EVs and other alternative fuel vehicles relative to incumbent internal combustion technologies.

As discussed above, a completed version of OMEGA v2.0 is not publicly available at the time of this drafting. The current demonstration version of the model uses share weight and price sensitivity parameters from the US-specific version of GCAM, and it has a limited set of vehicle classes. However, GCAM itself has been used in a variety of settings to model the adoption of a wider range of vehicle technologies in the context of global decarbonization (Kim, Waldhoff, & Edmonds, 2022; Kyle & Kim, 2011) as well as in the US specifically (Wise, Kyle, Dooley, & Kim, 2009).

For additional information on the OMEGA v2.0 model, refer to EPA (2022).

MA3T

Developed and managed by Oak Ridge National Laboratory (ORNL), the **Market Acceptance of Advanced Automotive Technologies (MA3T)** model is a demand-side vehicle choice model used to understand factors driving individual purchasing decisions in new vehicle technologies. The model includes 20 different powertrain technologies for each of five vehicle classes (i.e., small car, large car, small SUV, large SUV, and pickup). Within each of the powertrain technology classes, multiple variants exist to capture trade-offs between vehicle attributes amongst class options.

MA3T contains a rich and detailed representation of the US consumer LDV market, consisting of more than 9,000 different consumer segments based on six dimensions: (1) driving patterns; (2) new technology attitude; (3) population density; (4) US census division and state; (5) home charging convenience; and (6) workplace charging availability. Each segment faces the same number of powertrain options. Therefore, the model can provide a detailed representation of the US LDV market.

The basis of MA3T is a nested multinomial logit discrete choice model that endogenously predicts the purchase probabilities for different LDV technologies in the US out to the year 2050. The initial level of MA3T's nesting structure is a consumer choice between a passenger car and a light-duty truck. In the second level of the nest, consumers choose between the powertrains noted above. Purchase probabilities for each vehicle option and a given consumer segment depend on a series of value components, including vehicle attributes, driver behavior, infrastructure, and policies. Purchase probabilities for each segment are used to derive market penetration rates, vehicle sales patterns, vehicle population, fuel consumption, and annual life-cycle greenhouse gas (GHG) emissions. Other outputs produced by the model are annual government expenditures on vehicle subsidies and consumer surplus.

MA3T can be used to evaluate various policies such as tax credits, feebates, CAFE standards, carbon taxes, a low carbon fuel standard (LCFS), renewable fuel standards (RFS), and time of use (TOU) rates. Policy-relevant published work that uses MA3T includes an analysis of the impacts of Department of Energy hydrogen technology research targets and a novel regulatory pathway considered under the Renewable Fuels Standard (Lin, Dong, & Greene, Hydrogen vehicles: Impacts of DOE technical targets on market acceptance and societal benefits, 2013; Podkaminer, Xie, & Lin, 2017).

MA3T is continuously updated and recalibrated as more is learned about consumer preferences and advanced vehicle technologies. The most recent update to the model occurred in 2021. For additional information on the MA3T model, refer to Lin (2021); Lin, Dong, and Greene (2013); and Lin & Greene (2010).

LAVE-Trans

The **Light-duty Alternative Vehicle Energy Transitions (LAVE-Trans)** model was originally developed by ORNL and used in the National Research Council (NRC) 2013 study, *Transitions to Alternative Vehicles and Fu*els. Like MA3T, the LAVE-Trans model tracks the evolution of vehicle fleet efficiency and fuel use out to 2050, which includes the potential for increasing numbers of non-incumbent vehicle technologies to enter the fleet mix over time. The model represents major economic barriers that can impede this transition, including technological limitations, issues with scaling, and consumer risk aversion. Each barrier can be viewed as either a transition cost or an external benefit derived from adopting the new vehicle technology. LAVE-Trans incorporates each of these barriers, allowing for the quantification of the costs associated with overcoming these barriers, as well as the external benefits of policies used to overcome them.

The core of LAVE-Trans is a representative consumer choice model that uses a nested multinomial logit approach to estimate consumer purchase probabilities and derive vehicle market shares. In contrast to other NMNL approaches discussed previously, the first LAVE-Trans nest is whether the consumer opts to buy a vehicle; subsequent nests provide an increasingly granular representation of vehicle types and fuels. Nine variables determine market shares: (1) retail price equivalent; (2) energy cost per kilometer; (3) range; (4) annual maintenance cost; (5) fuel flexibility; (6) range limitation for BEVs; (7) availability of public charging infrastructure; (8) risk aversion (innovator vs. majority); and (9) diversity of make and model options available.

The model forecasts sales shares for two LDV classes (i.e., cars and light trucks) and six different powertrain choices, including conventional ICE, BEV, HEV, two PHEV classes, and fuel cell vehicles (FCV). The model captures the heterogeneity of consumers' preferences based on the inclusion of two consumer segments: early adopters and majority adopters. Early adopters are more risk-taking and will adopt new advanced vehicle technologies with less hesitation, whereas majority adopters are risk averse and will only come into the market as more of these new vehicle technologies are sold.

LAVE-Trans can model scenarios reflecting various policy options with the potential to affect consumer choices, including new vehicle rebate programs, mandates, incentives for fuel or charging infrastructure development, and fuel taxes. LAVE-Trans was used to study the market adoption of electric drive vehicles in response to a national embracing of California's Zero Emission Vehicle (ZEV) mandates, and LAVE-Trans modeling has played important roles in informing California Energy Commission (CEC) research (Greene, Park, & Lin, 2013; California Energy Commission, 2015).

For additional information on the LAVE-Trans model, refer to NRC (2013).

ADOPT

Developed by the National Renewable Energy Laboratory (NREL), the **Automotive Deployment Options Projection Tool (ADOPT)** is a vehicle consumer choice and stock model used to estimate the impacts of changes in vehicle technology cost and performance (e.g., cheaper EV batteries, vehicle light-weighting) on US LDV sales, energy use, and GHG emissions.

The vehicle market in ADOPT reflects LDV options as they exist today, from which future LDV options evolve endogenously by optimizing vehicle attributes for consumer preferences. Baseline model simulations begin with all existing vehicle makes, models, and trim levels available on the market, providing a realistic view of the market and an accurate starting point for vehicle attributes. ADOPT then estimates future vehicle sales by applying exogenous technology improvements and corresponding changes in vehicle attributes over time. This new set of options then flows into the consumer choice component of the model. A unique feature of ADOPT is that it is spatially explicit and can forecast vehicle sales at the zip code level.

Unlike many other vehicle choice models covered in this chapter, ADOPT does not use a standard MNL model to predict consumer choice but instead uses a ML model to estimate vehicle sales, applying a distribution of weighting coefficients via a sales distribution factor to key vehicle attributes, including price, fuel cost per mile, acceleration, fuel availability, vehicle size, and range. As discussed above, using a mixed logit model allows for increased representation of consumer preference heterogeneity. Historical data has revealed that attitudes about vehicle attributes are a function of income. ADOPT captures consumer preference variation by income with perceptions of vehicle attributes having a nonlinear relationship with changes in income.

ADOPT can be used to evaluate alternative policies, regulations, and mandates such as CAFE standards, ZEV mandates, tax credits, and vehicle subsidies. ADOPT was used in NREL's landmark Electrification Futures Study to project electric vehicle growth (Jadun, et al., 2017). It has also been used in a variety of CEC research settings, including recent updates to the statutorily mandated Integrated Energy Policy Report as well as to understand important tradeoffs in energy transition policy design (Ledna, Brooker, & Lee, 2022; Ledna, Muratori, Brooker, Wood, & Greene, 2022). The California Air Resources Board also incorporated the CEC's ZEV forecasting framework (using ADOPT) into its Emission FACtor (EMFAC) tool (California Air Resources Board, 2021).

ADOPT has been updated several times since its initial release, and the latest version of the model was publicly released in January 2020. For additional information on the ADOPT model, refer to Brooker et al. (2015).

PRIMES-TREMOVE

Price-Induced Market Equilibrium System (PRIMES) is a European-focused energy system model originally developed by the National Technical University of Athens and maintained by its E3MLab and E3-Modelling. PRIMES-TREMOVE, the transportation component of the model, solves for the partial market equilibrium between the demand and supply of transport services and projects the evolution of passenger and freight transport demand by transport mode and vehicle type (split by powertrain and fuels). The model covers all European countries and makes projections until 2070 in 5-year time steps.

The model represents consumer choice of technology and fuel type for new vehicles using a discrete choice model with a nested Weibull formulation—another functional form discussed in the discrete choice literature. PRIMES-TREMOVE develops a unit cost index, expressed in €/vehicle-km, that includes costs of purchasing and operating a vehicle as well as hidden costs such as range anxiety dependent on car performance and availability of refueling/recharging infrastructure. The model also accounts for elasticity of substitution among alternatives and weights these costs by indexes that reflect product maturity and consumer acceptance. As with NMNL, the model calculates sales shares on a nested basis, first between ICE, battery-based electric cars, and fuel cell cars and subsequently into more disaggregated technologies.

PRIMES-TREMOVE can model a wide range of policy measures, including EU taxation directives, the EU Emissions Trading System, and regulatory policies. The model has been applied in various European policy modeling contexts, including EC LDV GHG regulations and the EU 2050 long-term decarbonization strategy (European Commission, 2017; European Commission, 2022).

For additional information on the PRIMES-TREMOVE model, refer to E3 Modelling (2018; Siskos, Capros, & De Vita, 2015).

CHAPTER 4

Conclusion

Our literature review of LDV market forecasting models revealed that market diffusion models, consumer choice models, and agent-based models are common choices to project future vehicle sales. Each model has strengths and weaknesses that can make it more suitable for specific types of analysis.

Diffusion models are relatively straightforward to estimate but are limited to adoption of a single technology without competitors. They require exogenous specification of both the total available market share and the timeframe by which that market share is reached. As such, diffusion models are best used to understand the initial adoption of new-to-market technologies.

Once historical data or other consumer preference data is available, analysts can employ approaches like consumer choice and agent-based models, which can more richly represent consumer behavior in competitive markets. Consumer choice models are the most commonly used in the LDV adoption literature among all three model types we examined, often using a logit formulation as their basis. Consumer choice models are also easy to estimate and allow for competition between alternatives, but they can be sensitive to both the inclusion and values of explanatory variables used for their estimation. These choice models can represent a good compromise between the ease of estimation in diffusion models and the flexibility of ABMs, which is likely a reason they're so prolific.

While diffusion and consumer choice models can characterize individuals as part of broader markets, ABMs are "bottom-up" models representing individual agents' behavior. ABMs can include social processes and other non-monetary influences on adoption decisions. But the richness of ABMs comes at a cost: they are generally more difficult to design and estimate and can require a great deal of computational capacity. As the size of the market being estimated by the ABM grows, so too does the complexity and solve time—which can put ABMs out of reach for estimation of national-scale projections.

Promising work has merged several types of adoption models to benefit from their strengths. Struben and Sterman (2008) merged diffusion modeling with consumer choice modeling to estimate market adoption of alternative-fueled vehicles, while Cui et. al. (2011) use a consumer choice model as part of an agent-based modeling framework. Recently, Kinter-Meyer et. al. (2022) estimated distribution circuit-level adoption of EVs using a Bass diffusion approach followed by household-level adoption via a MNL model.

We found that government-funded models have widely adopted consumer choice techniques to understand how policies, regulations, and incentives can influence market adoption patterns of new LDV technologies—particularly in cases where competing technologies exist. These models vary in computational power, how they characterize the LDV market, and the types of vehicle attributes and demographic characteristics that drive projections of consumer preferences.

Because all the models we reviewed have strengths and weaknesses, policymakers need to be aware of the inherent limitations of the models they rely on to assess policy design and tradeoffs. The US and the world are still in the early stages of a transition to lower-emitting transportation technologies. The coming years will yield new data and insights as analysts observe how technology adoption trends come to pass in reality. These data and insights will improve researchers' ability to provide more accurate forecasts in the future. In addition, advances in computing capacity and academic achievement in model development are likely to yield improvements to today's suite of modeling options and new modeling approaches.

In the meantime, these models can provide useful, if imprecise, information as policymakers seek to advance this low-carbon transition.

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