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# Methods for Forecasting the Market Penetration of Electric Drivetrains in the Passenger Car Market

Current car technologies will not solve upcoming challenges of mitigating greenhouse gas emissions in road transport. Projections of the market penetration by alternative drive train technologies are controversial regarding both forecast market shares and applied scientific methods. Accepting this latter challenge, we provide a (so far missing) overview of methods applied in this field and give some recommendations for further work.

Our focus is to classify the applied methods into a convenient pattern and to analyse models from the recent scientific literature which consider the electrification of light-duty vehicles. We differentiate the following bottom-up approaches: Econometric models with disaggregated data (such as discrete choice), and agent-based simulation models. The group of top-down models are subdivided into econometric models with aggregated data (e.g. vehicle stock data), system dynamics, as well as integrated assessment models with general equilibrium models. It becomes obvious that some methods have a stronger methodological background whereas others require comprehensive data sets or can be combined more flexibly with other methods. Even though there is no dominant method, we can identify a trend in the literature towards data-driven hybrid approaches, which considers micro and macro aspects influencing the market penetration of electric vehicles.

Keywords: market penetration, electric vehicles, modelling, methods, diffusion, forecasting, alternative drivetrains

## 1 Introduction

Driven by the fast development of emerging economies, a doubling of the global fleet of light-duty vehicles (LDV) and fuel demand by 2050 is expected in business-as-usual scenarios (IEA (International Energy Agency), 2016a). When these LDV are still based on conventional drivetrain technology, this development is a strong contradiction to the current objectives of mitigating greenhouse gas (GHG) emissions in order to limit

global warming below the two-degree target, i.e. halve global GHG emissions until 2050 (IPCC, 2014). Currently, the transport sector, as the second largest emitter of the main GHG, carbon dioxide (CO<sub>2</sub>), increases its share significantly compared to the key player, the energy sector (IPCC, 2014). Therefore, its responsibility to reverse this trend is substantial. However, transport has not yet been in the focus of the political agenda (cf. Creutzig et al., 2015). Electric drivetrains (i.e. hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), pure battery electric vehicles (BEV), and fuel-cell electric vehicles (FCEV)) – besides the “servitization” of mobility – are considered backbones for sustainable transport systems. A successful market penetration of (partially) electrified vehicles seems highly probable (IEA (International Energy Agency), 2016b).

A preferably precise market forecast for alternative drivetrains is crucial for several decision makers in the automotive and energy industries as well as in politics. However, current predictions show diverse results (Kay, Hill, & Newman, 2013) but have become a very actively investigated research topic with a multitude of applied methods (Jong, Fox, Daly, Pieters, & Smit, 2004). According to most studies, the market forecast is (still) associated with unavoidable uncertainties and may in the early market phase depend strongly on policy incentives (Lévay, Drossinos, & Thiel, 2017). After a market share of around 2%, a distinct market take-off might occur (Golder & Tellis, 1997). Hence, at the current market phase the reliability of study results relies on many hazards and does not imply any unique solution. Nevertheless, the scientific community is in charge of providing suitable methods for generating these forecasts. In the following, we therefore give an overview of forecasting methods currently applied in this research area by classifying them and highlighting their strengths and weaknesses (similar to Anowar, Eluru, & Miranda-Moreno (2014) or Potoglou &

Kanaroglou (2008)). Our results might be used by researchers to find an appropriate method for answering their specific questions or by decision makers to evaluate the reliability of applied methods.

We structured our paper in accordance with the main methodological dimensions and start with a short introduction to the main terminology and methodological background before dedicating further sections to the specific methods. Section 3 gives an overview of current research into bottom-up models such as disaggregated econometric models (3.1), and agent-based models (ABM) (3.2). Section 4 deals with top-down models classified into econometric models (4.1), system dynamics (SD) models (4.2), integrated assessment models, and general equilibrium models (4.3). Finally, Section 5 presents some hybrid models, which are combinations of bottom-up and top-down models. A discussion and a section for conclusions complete the paper.

## 2 Proposed Classification of Methods

Methods applied in our research field can be classified by a multitude of dimensions.

We base our classification on the bottom-up and top-down model dimensions (cf.

Figure 1), which is a standard approach in the energy field (cf. Herbst, Toro, Reitze, & Jochem, 2012).

- **Bottom-up models** represent reality by aggregating heterogeneous characteristics of technological or socioeconomic activities and processes. They are calibrated with disaggregated data and mostly focus on a single economic sector. The methods are based on simulations or optimization techniques.
- **Top-down models** apply macroeconomic theory, econometric and optimization techniques with aggregate economic variables. They rely on historical data of

consumption, prices, incomes, or factor costs and may consider all main economic sectors such as energy, transportation, agriculture, and industry. Some top-down models incorporate technology data, thus narrowing the gap to bottom-up models.

- **Hybrid models** are a combination of bottom-up and top-down models, thus representing an example of mixed modeling (Hourcade, Jaccard, Bataille, & Gherzi, 2006).

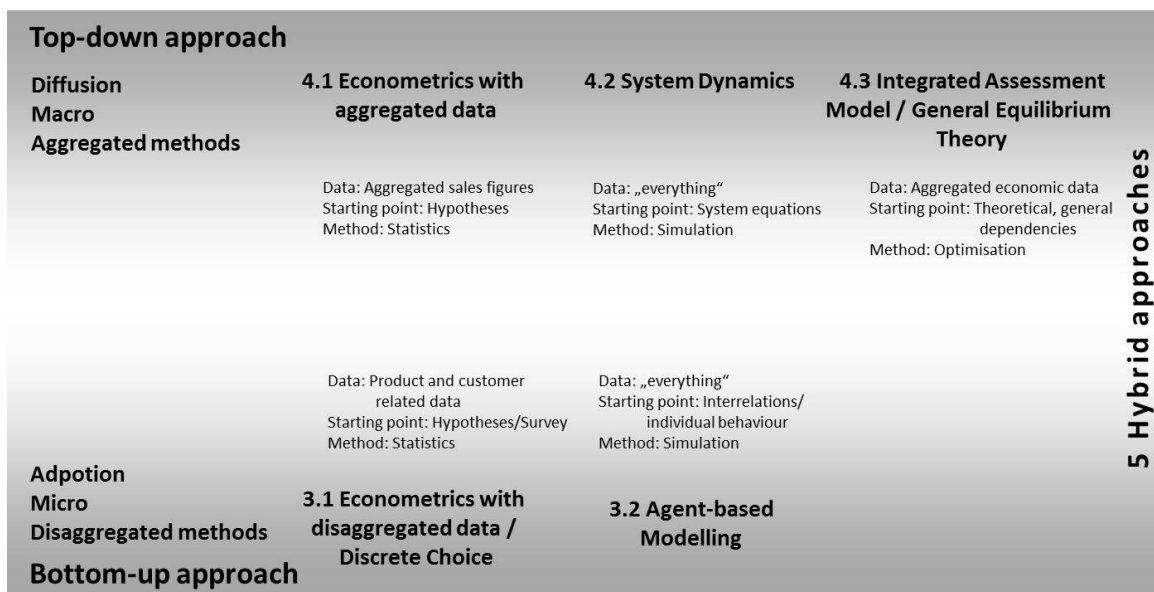


Figure 1: Outline of the considered methodology

Besides this general modeling differentiation, the availability of data has a crucial influence on the choice of methodology. The most apparent influence on the modeling technique is the aggregation level of the data. Furthermore, the quality of the data is highly relevant. In the transport sector, most data is available only on a monthly or annual basis. An exception includes e.g. fuel prices, which are available at least on a daily basis. While aggregated data such as vehicle sales are often publicly available, detailed data availability is often restricted to commercial users. Especially data on customer requirements is costly, highly sensible, and difficult to access. The quality of

each dataset should be crucially evaluated with respect to data consistency and reliability.

Another significant peculiarity in our field of investigation is the heterogeneity of car purchase decisions. Actors in different submarkets have specific objectives: Whereas, for company fleet vehicles, a rational decision rule is prevalent for the purchase decision (Brand, Cluzel, & Anable, 2017), individual purchase decisions in the company car market are diverse. Private customers, who in Germany represent about 40% of the whole LDV market (Gnann, Plötz, Funke, & Wietschel, 2015), have individual preferences and show even aspects of bounded rationality in their decisions, which highly rely on (spontaneous) heuristics and cognitive rules of thumb but hardly on analytical deliberation (de Haan, Mueller, & Scholz, 2009). Consequently, a simple reproduction of the vehicle purchase decision seems to be impossible.

Nevertheless, pure cost optimizing approaches are sometimes used for giving a first approximation of the market potential of an alternative technology (Pfahl, Jochem, & Fichtner, 2013). Many car ownership models refer to this input parameter, which is often based on the total cost of ownership (TCO) or the life-cycle cost approach. Hence, all costs such as taxes, maintenance and investment during the whole life cycle are considered and converted into comparable units such as euros per year. These comparisons usually rely on assumptions (e.g., for annual mileage, fuel price prognosis for several years, etc.) which have a significant impact on results. Cost-optimizing approaches are often applied in energy system modeling (Densing, Turton, & Bäuml, 2012; Grahn et al., 2009; Gül, Kypreos, Turton, & Barreto, 2009; D. McCollum, Yang, Yeh, & Ogden, 2012; Pietzcker et al., 2014).

### **3 Bottom-up Models**

In our research field, bottom-up models have a long tradition – mainly in econometrics

(cf. Section 3.1). A more recent development is agent-based modeling (ABM) (cf. Section 3.2). Mixed bottom-up models are applied, too (Mock, Hülsebusch, D., Ungethüm, J., & Schmid, S.A., 2010; Propfe, Kreyenberg, Wind, & Schmid, 2013; Shafiei et al., 2012; Sullivan, Salmeen, & Simon, 2009; Vliet, Vries, Faaij, Turkenburg, & Jager, 2010).

### ***3.1 Econometric Models with Disaggregated Data***

In this section, we focus on methods from applied microeconometrics.

#### *History*

McFadden (2000) provides an overview of the history of microeconomic analysis of choice behaviour by consumers who face discrete economic alternatives. Research concerning transportation decisions has been further enriched afterwards by Abou-Zeid and Ben-Akiva (2014). Furthermore, discrete choice models were widely applied to microeconomic decisions concerning vehicle choice including alternative fuels and drivetrain technologies (Achtnicht, Bühler, & Hermeling, 2012; Brownstone, Bunch, & Train, 2000; Brownstone & Train, 1998; Bunch, Bradley, Golob, Kitamura, & Occhiuzzo, 1993; Dagsvik, Wennemo, Wetterwald, & Aaberge, 2002; Daziano, 2015; Daziano & Achtnicht, 2014; Daziano & Bolduc, 2011; Hensher, Beck, & Rose, 2011; Horne, Jaccard, & Tiedemann, 2005; Train, 1986). Another recent development is the random regret minimization (RRM) model introduced by Chorus, Arentze, & Timmermans (2008).

The economists' standard microeconomic model, a theory of rational choice, has been further developed by integrating psychological factors that are included in decision-making (Moshe Ben-Akiva et al., 1999). In psychological theories of the choice process, the individual is less organized, more adaptive and imitative. Attitudes

play a major role (Kahneman & Tversky, 2000). These are determined by affect and motivation and influence perceptions that feed into the choice process. Utility maximization or, alternatively, regret minimization by individuals is reduced to one of many factors in the decision-making environment. Its influence is often constrained by context effects, emotion, and errors in perception and judgement (Gärling, 1992; Loewenstein, 1996; Svenson, 1979). Heuristic rules seem appropriate to describe decision-making processes of humans. The psychological point of view concerning the adoption of alternative fuel vehicles has been widely studied during the last years (Axsen, TyreeHageman, & Lentz, 2012; Egbue & Long, 2012; Peters, Gutscher, & Scholz, 2011; Schuitema, Anable, Skippon, & Kinnear, 2013).

#### *Main characteristics and assumptions*

According to Ben-Akiva et al. (2002), domains of choice research can be classified by (1) Behavioural Choice Analysis, (2) Predictive Choice Models, and (3) Random Utility Models. Predictive choice models focus mainly on quantitative modeling in order to use relevant results for predictions that are of particular interest in economics, marketing, planning, and engineering. According to Ben-Akiva et al. (2002), behavioral choice analysis deconstructs the choice process by concentrating on revealing irregularities and idiosyncratic features of choice behavior. Modeling of choice behavior by incorporating cognitive processes with unobserved or latent elements of choice processes in predictive choice models, e.g. attitudes and perceptions within structural equation models, is done by hybrid choice models (Abou-Zeid & Ben-Akiva, 2014), hybrid discrete choice models (Raveau, Yáñez, & Ortúzar, 2012) or integrated choice and latent variable models (Bhat & Dubey, 2014; Vij & Walker, 2016). The main assumption is that there is a rationale behind all choices, which can be approximated by utility maximization or, alternatively, regret minimization. Due to the applied statistical methods, data



requirements are substantial.

### *Literature*

There is a comprehensive literature on disaggregated econometric models in our research field. We therefore focus in Table 1 on more recent models. A problem-focused introduction is given by Daziano & Achtnicht (2014) and further literature can be found in (Al-Alawi & Bradley, 2013).

Table 1: Selected literature on econometric models with disaggregated data

Authors	Jurisdiction	Time horizon	Technology	Key features
Plötz et al., 2014	Germany	-	BEV, PHEV	Consumer-choice modeling is applied focusing on early adopters of EVs.
Lopes et al., 2014	Portugal / Lisbon	2020	EV	A rule-based screening methodology with simple non-compensatory rules is developed. Results suggest that, currently, the diffusion of EV in Lisbon Metropolitan Area is very restricted.
Glerum et al., 2014	Switzerland	-	BEV	A hybrid choice model based on a stated preference survey was specified for car purchase decisions which includes a forecasting analysis. As a result, they give certain properties of target customers.
Daziano and Achtnicht, 2014	Germany	-	HEV, LPG/CNG, biofuel, BEV, FCEV	Bayes estimates of a multinomial probit model with fully flexible substitution patterns are used in order to forecast consumer response to ultralow emission vehicles. Stated preference data from a Germany-wide survey of potential 600 light-duty vehicle buyers are used to estimate choice probabilities of different drivetrain alternatives.
Rezvani et al., 2015	US, UK, Denmark, Germany, Belgium, Netherlands, China	-	BEV, PHEV	A literature review is provided. The factors influencing consumer intentions to purchase EVs are the focus of this paper.

### *Discussion*

In order to classify the econometric-based electric vehicle adoption research of the last years, the literature from Table 1 and from Rezvani et al. (2015) are classified according to the scheme on domains of choice research by Ben-Akiva et al. (2002). As our study tries to identify methods to forecast electric vehicle market shares, we extended the framework by integrating (representative) market forecast models into the scheme (cf. Figure 2).

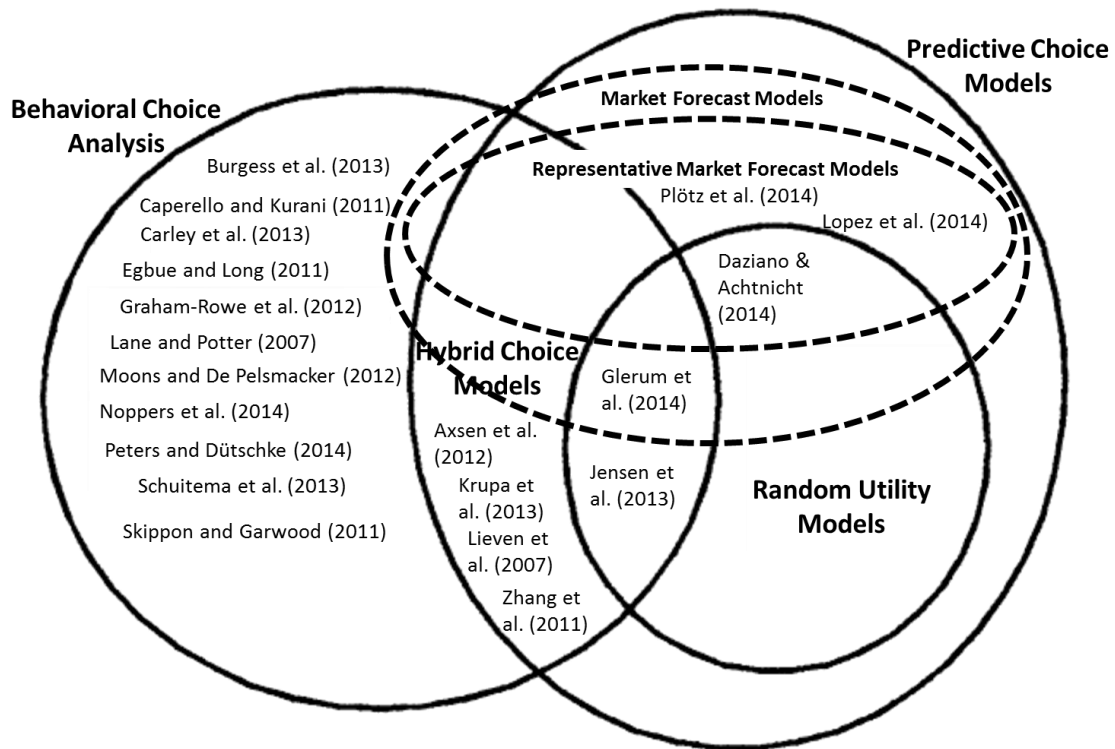


Figure 2: Categorization of econometric-based adoption studies of electric vehicles based on Ben-Akiva et al. (2002)

From Figure 2 follows that there are many studies on adoption of electric vehicles particularly accounting for psychological factors such as attitudes and perceptions. However, there is a lack of adoption studies incorporating these psychological factors in order to perform market forecasts.

Table 2: Advantages and disadvantages of disaggregated econometric models

ADVANTAGES	DISADVANTAGES
<ul style="list-style-type: none"> <li>Market diffusion scenarios based on revealed or stated preferences can be <u>empirically modeled</u> already at an early market stage by applying inferential statistics.</li> <li>Market behavior can be explained by <u>aggregating the single decisions of individuals</u> taken from discrete choice models. Therefore, (regional) heterogeneities might be taken into account.</li> <li>Desirable <u>combination of theory and empirical basis</u>.</li> </ul>	<ul style="list-style-type: none"> <li><u>Snap-shot</u> of preferences at the point of time of the survey. Therefore, the method is more suitable for short time horizons (which is less relevant in the context of the deployment of new vehicle technologies).</li> <li>High <u>costs</u> for representative data collection.</li> <li><u>High quality requirements</u> for survey design and representative data collection to assure a suitable generalization.</li> </ul>

Advantages of disaggregated econometric data and models (cf. Table 2) include that diffusion of innovations can be modeled already at an early market stage.

Furthermore, market behavior can be explained as diffusion is represented by an aggregation of individual choices. However, the preferences collected during surveys only represent snap-shots accompanied by high costs and quality standards for collecting representative data.

### ***3.2 Agent-based Modeling***

Existing reviews of diffusion models such as those presented by Al-Alawi and Bradley (2013) or Coffman, Bernstein, and Wee (2015) have revealed an increasing interest in the possibilities provided by ABM in this field of research.

#### *History*

ABM and individual-based simulation have its origin in the late 1940 when computational analysis became practicable for research disciplines. Its roots can be found in the modeling of cellular automata, as well as in the various fields of artificial intelligence (G. N. Gilbert, 2008). ABM is mainly based on its basic components, the agents (and their agent theory), the representation of the complexity of the modeled system (e.g. interaction topology), and the emerging states after simulation of the model and has been developed simultaneously in many research fields ranging from social and economic sciences to natural sciences. Consequently, there is no unique definition of ABM.

#### *Main characteristics and assumptions*

The main objective of simulation is describing and subsequently analyzing the (global) behavior of dynamic complex systems by means of imitation of real processes or systems over a specified period of time. If these simulations represent systems that are characterized by decentralized and distributed data as well as asynchronous

computations (absence of a central control), it is preferable to use an agent-based approach. One main advantage of ABM is their (up- and down-) scalability and thus an accordingly easy disassembly of the complex system. ABM consists of three main components: Agents, an interconnecting structure, and their context. The context comprises all necessary external information which is not stored within the agents and is not to be confused with the environment outside of the system. It is defined by the totality of the agents of the system, their individual characteristics, system rules, existing goods, and sensors. Although the definition of agents varies between research fields, the main properties of agents are: Individuality and ability to communicate (Hewitt, 1977), cognition of their environments, proactivity, and independence (Wooldridge & Jennings, 1995). Agents may possess static or changing roles (which requires a certain ability to learn) and act charitably, competitively or in a team. The interactions of the agents in their particular contexts may lead to a global behavior (which may be regularities or patterns) within the model. This emergence allows identifying regularities for the modeled complex system.

With these properties, ABM and its agents are predestined to simulate human relations and behavior (Rai & Henry, 2016). These flexibilities in modeling agents individually provides a wide range of opportunities to represent distinct behaviors such as strategies, bounded rationality or incomplete information (Sycara, 1998). Consequently, the data requirement is dependent on the research focus.

### *Literature*

Recently, the advantages of ABM have been used widely to forecast the market penetration of alternative drivetrains in the passenger car market. One cornerstone for these diffusion models was provided by Kiesling, Günther, Stummer, & Wakolbinger, (2012). Depending on the objective, simulations run with different time horizons from

about 10 years (cf. Table 3). Many ABM diffusion models discuss PHEV adoption (Cui et al., 2010; Eppstein, Grover, Marshall, & Rizzo, 2011; Stephens, 2010; Sullivan et al., 2009). Diffusion of BEV and other drivetrains (de Haan et al., 2009; Schwoon, 2006), other fuels (e.g. Vliet et al., 2010) or even in combination with charging infrastructure (Gnann, 2015) are analyzed. Many ABM focus on a low level of aggregation and on local residential diffusion (e.g. Cui et al., 2010) or regions with restricted scope (e.g. Knox County (Cui et al., 2010), Boston (Brown, 2013), Michigan (Stephens, 2010), Iceland (Shafiei et al., 2012), Germany (Propfe et al., 2013) or Hawaii (Coffman et al., 2015)). Some ABM are based on the individual parameterization of the agents (e.g. budgets, recharging concerns, previously owned cars) and the vehicles (e.g. size, performance, and brand) (Mock et al., 2010; Propfe et al., 2013; Shafiei et al., 2012; Sullivan et al., 2009). Garcia (2007) uses an individual hedonic demand model developed by Boyd et al. (1980). Several ABM included a multitude of external impacts on the purchase decision like spatial (Eppstein et al., 2011) and neighborhood (Cui et al., 2010) effects, social networks (de Weerd, Zhang, & Klos, 2012), media influences (Eppstein et al., 2011), and infrastructure (Schwoon, 2006). ABM allows integrating multiple actors (besides the agent group of adopters) that may influence the market penetration. Such actors are e.g. car manufacturers and the government (Garcia, 2007). These additional agents equally pursue an objective and have a range of possible actions that influence the simulation run. In several of the reviewed ABM, market penetration is a secondary aim. Other objectives are e.g., the impact of the new fleet composition on the energy system (Cui et al., 2010) and on GHG emissions (Stephens, 2010) or determining the effect of car purchase incentives (de Haan et al., 2009). Due to the object-based architecture of ABM, they are often applied in hybrid models (e.g. Brown, 2013; Kieckhäfer, 2013).

Table 3: Selected literature on agent-based models of adoption

Authors	Jurisdiction	Time horizon	Technology	Key features
Brown, 2013	Boston metropolitan area	2009-2030	PHEV, BEV	A mixed logistic regression and an agent-based model are combined to simulate social network interactions. Battery costs have a relatively small impact on EV diffusion in comparison to policy, range, miles per gallon (MPG), and vehicle miles traveled.
Propfe et al., 2013	Germany	2010-2030	FCEV, BEV, PHEV, HEV	The analysis is based on three fleet scenarios within the VECTOR21 (vehicle technology scenario model) model. Results highlight that EV penetration depends mainly on external conditions.
Shafiei et al., 2012	Iceland	2012-2030	EV	The model is based on a vehicle choice algorithm that accounts for social influences and consumers' attractiveness for vehicle attributes. The evaluation focuses on the effects of fuel and vehicle prices as well as charging concerns. As a conclusion, successful adoption of EV needs policy support in adverse scenarios.
Eppstein et al., 2011	US	25 years	PHEV	A spatial vehicle consumer choice model is developed which explores sensitivities and nonlinear interactions of the vehicle purchase decision. The results indicate that PHEV market share can be increased by presenting estimates of expected lifetime fuel costs to customers.
Zhang et al., 2011	US	multiple time horizons	alternative fuel vehicles, PHEV, BEV	A choice-based conjoint analysis is used to elicit heterogeneous consumer preference. As a core result, positive word-of-mouth messages lead to a higher willingness to pay for alternative fuel vehicles.
Cui et al., 2010	Knox County,	2011-2020	PHEV	The analysis is based on a spatial distribution of car ownership at local residential household level. The main result highlights that neighborhoods with multiple PHEV may require changes in distribution grid infrastructure.
Stephens, 2010	Michigan	2010-2030	PHEV	This study is based on travel demand and statistical information on travel by U.S. drivers and highlights the electricity and fuel demand and the resulting GHG emissions.
Vliet et al., 2010	11 populations of motorists	20 years	6 fuels blends from 6 feedstocks	The model is based on heuristics and considers different vehicles as well as social attributes. As a result, price is the main decision criterion for motorists.

de Haan et al., 2009	Switzerland	-	fuel-efficient and highly inefficient cars	Consumer agents possess price elasticities and behavioral options to react to feebates. These systems seem to successfully reduce energy consumption and CO <sub>2</sub> emissions.
Stephan and Sullivan, 2009	US	2015-2040	PHEV	Two types of agents are considered: Vehicle owners and hydrogen fuel suppliers. Results show that subsidies are critical and sales tax exemptions can help if manufacture subsidies are in place.
Garcia, 2007	US	-	PHEV, BEV	The combination of a consumer behavior model and an ABM is applied in order to analyze the impact of manufacturers' product design and vehicle offerings on market development.

### Discussion

On the one hand, the lack of a commonly acknowledged definition of ABM leads to a diversity of models, which makes an objective evaluation challenging. On the one hand, this flexibility allows a comprehensive adjustment to the system under evaluation or even to extend the model by other methods (hybrid model). The interactions among agents and with the environment (including learning) are in the focus of this methodology, which allows to represent decision patterns close to reality (cf. Table 4).

Table 4: Advantages and disadvantages of agent-based modeling

ADVANTAGES	DISADVANTAGES
<ul style="list-style-type: none"> <li>• Specific and <u>heterogeneous market behavior</u> of different actors can be considered (behaviors can be defined discretely and may change over time).</li> <li>• Modular character of the methodology allows combinations with other methods into <u>hybrid models</u>.</li> <li>• <u>Learning</u> and strategies can be applied.</li> <li>• Relationships and <u>interactions</u> of the systems' actors can be modeled precisely.</li> </ul>	<ul style="list-style-type: none"> <li>• The freedom in modeling leads to <u>less transparent methods</u>.</li> <li>• Models tend to be incomprehensible, and <u>complex</u> computational modeling experience is required compared to typical formal proofs; <u>there is no standardized toolbox</u>, yet.</li> <li>• Due to a <u>weak theoretical background</u> it is hard to follow all assumptions and further model specifications.</li> <li>• <u>Data basis</u> is in most models too weak for calibrating the behavioral rules of agents.</li> </ul>

## 4 Top-down Models

We subdivide the section into econometric models (Section 4.1), system dynamics models (Section 4.2), and integrated assessment and general equilibrium models



(Section 4.3). Mixtures of top-down approaches are not known.

#### ***4.1 Econometric Models with Aggregated Data***

In this section, we focus on methods from applied macroeconometrics.

##### *History*

Following early econometric work on business cycles, econometric activity unfolded at the beginning of the last century (Morgan, 2008) and was institutionalized in the 1930s. It aimed “*at a unification of the theoretical-quantitative and the empirical-quantitative approach to economic problems*” (Frisch, 1933, p. 1). Important original contributions had been made by, among others, Tinbergen (1937), Haavelmo (1944), and Koopmans (1949). Over the years, econometrics has arguably become the dominant method within empirical economics.

##### *Main characteristics and assumptions*

A variety of econometric methodologies has been proposed (cf. Gilbert, 1986; Pagan, 1987; Hoover, 2005). With a focus on market penetration of electric vehicles, four key aspects of aggregate econometrics modeling are highlighted. (1) **Forecasting**, which is a main purpose of most work in econometrics (Intriligator, 1983). (2) **Time series**, which include causal models and ‘sophisticated’ extrapolative models, which are based on techniques popularized as the Box-Jenkins approach (Box & Jenkins, 1976). (3) **Stochastic modeling**, which acknowledges the random nature of economic variables explicitly in models and relies on statistical inference (Spanos, 1999). (4) **Data quality**, which is always a crucial issue in econometrics (Morgenstern, 1965; Griliches, 1986).

For multi-country forecasts, three potential problems can be highlighted with regards to vehicle-related data: Short available time horizon for alternative drivetrains,

lack of harmonization of variables' definitions, and changes over time in the data collection method by the statistical agency.

### *Literature*

Two lines of application of aggregate econometrics in the car market are considered: Car ownership projections and choice of vehicle types. Aggregate econometric models have been extensively used to forecast car ownership at the national level (Jong et al., 2004). Modelers have long been aware of car market saturation and have consequently employed nonlinear sigmoid functions to capture how car ownership changes over time. Initially, the modeler determines whether a symmetric curve should be applied. The former results in the Verhulst growth or logistic (regression) model (Verhulst, 1838). In theory, many different asymmetric S-shaped growth curves could be used: A common one is the Gompertz growth curve used by e.g., Dargay et al. (2007). In our context of diffusion of innovations, the Bass model (Bass, 1969, 2004) is often applied. Relaxation of its most restrictive assumptions has led to several variants of the Bass model. Some authors even extend the Bass model with disaggregated data (e.g. Higgins et al., 2012). The task described in this paper, however, is a different one, as we are not only interested in forecasting a particular level of total car stock, but in the different market shares by type of car technology. To our knowledge, only few econometric models with (a short history of) aggregated data have been accomplished yet in our research field (e.g. Ensslen, Ringler, Jochem, & Fichtner, 2014; Jeon, 2010; McManus & Senter, 2009; Plötz, 2011) (cf. Table 5). McManus & Senter (2009) might be highlighted as a convincing application.

Table 5: Selected literature on econometric models with aggregated data from adoption

Authors	Jurisdiction	Time horizon	Technology	Key features
Dargay et al., 2007	45 countries	2002 – 2030	Overall vehicle stock	Gompertz model estimation based on pooled time series and cross-section data. Projections show that vehicle ownership will increase from 800 million in 2002 to over 2 billion in 2030.
Romilly, Song, & Liu, 1998	Britain (England, Scotland and Wales)	1990 – 2025	Overall vehicle stock	Model estimation based on time series data from 1953-1994 initially including seven exogenous determinants of car ownership. Long-range forecasts are comparably low (416 vehicles per 1000 citizens in 2025).
Ensslen et al., 2014	Germany	2030	EV	The Bass diffusion scenario estimation is based on EV stock data from 2009 until 2013 and the assumption that there will be 5 million EV on German roads by 2030.
Jeon, 2010	US	2009 – 2030	HEV	The Norton-Bass model estimation is based on time series data of first generation Toyota Prius from 2001 – 2008. Sales forecasts for four generations of HEV are projected Fourth generation HEV sales reach about 5 million in 2030.
McManus and Senter, 2009	US	2010 – 2050	PHEV	Six different PHEV market diffusion models are applied: Bass, Generalized Bass, Logistic, Gompertz, Centrone additionally using demographic factors, and a rather complex dynamic system model accounting for consumer criteria and factors related to consumer choice.
Plötz, 2011	Germany and US	2010 – 2045	HEV, PHEV, BEV, ICEV	The Lotka-Volterra model is applied. The results focus on the competition between EV and HEV.

### *Discussion*

Given our purpose and the initial market conditions at the present time, aggregate methods represent a rather unsuitable approach to this task in the current market phase with only limited historical data series available (cf. Table 6). Instead, disaggregate econometric models analyzing discrete choices might be preferred. However, as observed data becomes increasingly available, the aggregate econometrics method is expected to become increasingly useful for gaining insights into the prospects of vehicle technology market development. For short-term forecasting using monthly data, the Box-Jenkins approach may already deliver accurate forecasts.

Table 6: Advantages and disadvantages of econometric models with aggregated data

ADVANTAGES	DISADVANTAGES
<ul style="list-style-type: none"> <li>• Desirable <u>combination of theory and empirical basis</u>.</li> <li>• The method may be used to precisely quantify new <u>(economic) relationships</u>.</li> <li>• The method <u>emphasizes testing and facilitates the testing of hypotheses</u>.</li> </ul>	<ul style="list-style-type: none"> <li>• The method <u>relies on the availability of extensive high quality data</u> (the lack of historical data in our topic results in an overreliance on stated preference data and disaggregated econometric modeling).</li> <li>• Its strength is rather in <u>short time horizons</u> (which is less relevant in the context of the deployment of new vehicle technology).</li> <li>• <u>Regional specialties</u> are hard to consider due to lack of data.</li> <li>• There is a risk for model misspecification and inadequate statistical inferences.</li> </ul>

## 4.2 System Dynamics Models

System dynamic (SD) represents an alternative approach to modelling car technologies uptake.

### *History*

SD started to be developed by Jay W. Forrester in 1956 (Forrester, 1995), five years before his seminal work *Industrial Dynamics* (Forrester, 1961) was published. Although initially conceived for solving corporate problems, SD proved to be successful in its application to other social and environmental problems, regardless of whether the focus was local or global. This was reflected in works such as *Urban Dynamics* (Forrester, 1969) and *World Dynamics*, which introduced the SD model known as WORLD1 (Forrester, 1973). The global modeling exercise reported in *The Limits to Growth* (Meadows, 1972) perhaps remains the most famous application of the SD approach to date. Because of its emphasis on the endogenous point of view and feedback processes (Richardson, 2011), SD is regarded as a useful approach to understand complex dynamic systems.

### *Main characteristics and assumptions*

Mathematically, SD models are sets of ordinary differential equations which can be

computationally solved as approximations by numerical integration methods such as Euler or Runge-Kutta. For applications in the research field of market penetration of EV, the following five features of SD models can be highlighted. (1) Dynamic modeling, the explicit consideration of the independent variable ‘time’ is crucial in SD models. Investigation of the future market penetration of new technologies, preferably on a yearly basis, necessarily requires this approach. (2) Explanatory model for simulating behavior, is a key aspect in SD models (Bossel, 2007). SD modeling entails computer simulation, by which ‘what-if’ questions can be answered as if it were a controlled experiment. (3) Feedback process, where an input variable affects the output, but this also impacts (feeds back) the input after a time lag. From a consumer perspective, it is expected that important feedback loops affect the buying behavior of potential adopters, e.g. when they get more acquainted (through time) with new technologies by having the chance to use them or through peer effects. The explicit incorporation of feedback processes is at the core of SD modeling. (4) Long model time horizons, usually longer than 20 years are considered. An underlying premise is that, for most systems, the patterns of behavior can be fully visualized only when the appropriate (long-term) horizon is considered. (5) Delays, i.e. the existence of significant time lags between variables – similar to econometrics – is assumed. The data requirement depends on the research question.

### *Literature*

SD is versatile as it enables the integration with other approaches. We identify three common mixed modeling approaches within the SD framework. Firstly, the embedment of discrete choice frameworks (cf. Section 3.1) within SD models for reflecting choice behavior is often applied. In this framework, individuals do not interact; thus a diffusion framework is often included as complementary, in an attempt to capture interactions.

Secondly, Bass diffusion frameworks (cf. Section 4.1) are incorporated for simulating the diffusion of different vehicle drivetrains (e.g. Sterman, 2000). This example contains two stock variables (*Potential Adopters* and *Adopters*), connected by a single flow variable (*Adoption Rate*), and illustrates three feedback loops: Two of them are negative feedbacks reflecting ‘market *saturation*’ and the third is positive, reflecting the effect of ‘*word of mouth*’. Thirdly, hybrid models, e.g. combining SD and ABM, have been developed. From the perspective of the automobile industry, a combination of market chances (SD) and concrete purchases (ABM) indicates an attractive modeling approach (see Weikl, 2010; Wansart, 2012; Jensen et al., 2016; Kieckhäfer et al., 2014). Table 7 provides an overview of SD studies for the purpose of investigating the market penetration of alternative LDV technologies. Ford (1995) provides an influential paper in our research field.

Table 7: Overview of selected SD literature on market penetration of electric vehicles

<b>Authors</b>	<b>Jurisdiction</b>	<b>Time horizon</b>	<b>Technology</b>	<b>Key features</b>
Ford, 1995; Ford, 1999; BenDor and Ford, 2006	US (California)	20 years	CNG, HEV, EV	Drawing from the results of (Bunch et al., 1993), an SD model for analyzing a feebate scheme was built. The purchase decision is based on a multinomial logit (MNL) framework that includes six main attributes.
Schade, 2005; Krail, 2009; Fiorello et al., 2010	EU27, Switzerland, Norway	2050	HEV, CNG, LPG, FFV, BEV, FCEV	ASTRA (ASsessment of TRAnsport Strategies)'s vehicle fleet module is affected by population change and disposable income. The vehicle fleet models (VFT module) include a discrete choice component. The development of technologies and ageing of vehicles is considered. There are several feedbacks between and within the modules.
Purwanto, 2013	57 world regions	2050	HEV, CNG, LPG, BEV, FCEV	The MOVEET (MObility, Vehicle fleet, Energy use and Emissions forecast Tool) [former GLADYSTE, based on TREMOVE] model consists of four interrelated modules: "Transport Demand", "Environmental", "Welfare", and "Fleet". The latter contains a vehicle structure by type and technology. A nested logit computes mode shares. The shares of vehicles sold depend on GDP, acceleration time, fuel and non-fuel costs, and other parameters.
Struben and Serman, 2008	US (California)	60 years	HEV, CNG, Biofuels, FCEV	The model considers feedback from consumers' experience as well as word-of-mouth, marketing and network effects focusing on alternative drive trains. A simulation of learning, technological spillovers, and spatial coevolution of fueling infrastructure adds additional feedbacks that condition the diffusion process. The choice modeling is based on a standard multinomial logit (MNL) framework.
Meyer, 2009	Germany, Japan	2035	HEV, CNG, BEV, FCEV	Partially building on previous work by (Ford, 1999), the author deals with the German and Japanese markets. Vehicle aging chains are used and ten different utility coefficients are considered. In addition, other exogenous factors affect the market share by type of vehicle.
Walther et al., 2010	US (California)	2021	ZEV	The authors consider four interacting modules: "GHG and ZEV regulations", "Automotive industry", "Customers", and "Vehicle stock and infrastructure". Consumer awareness affects the choice of powertrain. This is based on an extended Bass model that represents the processes of 'word-of-mouth', 'oblivion' and marketing efforts. This influences consumers' choice set which, together with the assumed preferences, determine the market share of powertrains and segments.

Keith, 2012	US	2050	CNG, HEV, PHEV, BEV	A nested multinomial logit (NMNL) model is applied to describe the decision-making process. Vehicle choice results from the utility that the consumer derives for each platform, as a function of purchase price, operating cost, emissions and range. In addition, the concept of familiarity with different platforms is employed.
Shepherd et al., 2012	UK	2050	PHEV, BEV	Building upon the work by (Struben & Sterman, 2008), (Shepherd et al., 2012) modeled EV uptake using choice values estimated by (Batley, Toner, & Knight, 2004). The main factors considered were purchase price, operating costs, maximum speed, fuel availability, emissions, and range.
Pasaoglu et al., 2016	EU28	2050	LPG, CNG, Biofuels, HEV, PHEV, BEV, FCEV	The model consists of representative market agents. The following utility criteria are used to model the purchasing decision on the type of powertrain: Environment, performance, reliability, safety, convenience, popularity, choice, and cost. Using the idea of 'willingness to consider' (WtC) a given powertrain, based on Struben and Sterman (2008), a user's 'consideration set' is derived.

### Discussion

SD represents a suitable method to investigate system-wide effects. This appears to be a desirable feature when modeling the uptake of electric vehicles, which takes place within a complex socio-technical system. By its nature, the method simulates relationships at a rather highly aggregated level. However, examples exist of work that combines this system-wide aggregate approach with the disaggregate method. This is currently a fruitful line of research in the context of car technology market penetration (cf. Table 8).

Table 8: Advantages and disadvantages of system dynamics models

ADVANTAGES	DISADVANTAGES
<ul style="list-style-type: none"> <li>• Disequilibrium processes can be modeled explicitly.</li> <li>• The method supports nonlinear simulation over <u>long time horizons</u>.</li> <li>• There exist several <u>standardized toolboxes</u> for implementing SD approaches.</li> <li>• There were considerable improvements with regard to <u>transparency</u>; e.g. dimensional consistency checks and a high level of</li> </ul>	<ul style="list-style-type: none"> <li>• Method's <u>pragmatic approach</u> to analysis of historical data (usually without econometric methods) mixed with other assumptions makes the method subject to criticism.</li> <li>• Due to a <u>weak theoretical background</u> it is hard to follow all assumptions.</li> </ul>



transparency, reproducibility and communication (Martinez-Moyano, 2012), (Rahmandad & Sterman, 2012).	
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### ***4.3 Integrated Assessment and General Equilibrium Models***

Integrated assessment models (IAMs) are widely applied in interdisciplinary environmental sciences for global projections in the field of energy and climate change (e.g. (IPCC (Intergovernmental Panel on Climate Change), 2014). The macroeconomic part of these models might be based on general equilibrium models, which are based on economic theory. They use aggregated economic data and are usually focused on the impact analysis of policy instruments, changes in technology or other external factors. Therefore, only this part of integrated assessment models is of interest here. Today, most general equilibrium models also include microeconomic data and are therefore seen as bottom-up models or hybrid models (Böhringer & Rutherford, 2008). Nevertheless, we keep them in our top-down classification.

#### *History*

The concept of economic equilibrium lies at the heart of general equilibrium models. Not before the 1960s, when computational analysis became common for all research disciplines, economic equilibrium models developed from pure mathematical calculations with few empirical-based data to empirical-data based models. This was the hour of birth of computable general equilibrium (CGE) models (e.g. Harberger, 1962), which are widely used today in applied macroeconomics (Shoven & Whalley, 1984). More recent developments are Spatial or Dynamic Stochastic General Equilibrium Models (DSGE). Recently, DSGE models have been subject to not insubstantial criticism (cf. Caiani et al., 2016). Integrated assessment models have a long history in environmental sciences and are currently under comprehensive development. For

vehicle choice modeling, they are being extended by many behavioral features (cf. McCollum et al., 2016).

#### *Main characteristics and assumptions*

CGE models are mainly based on data from the system of national accounts or the input-output matrix (Miller & Blair, 2009) and can have microeconomic foundations such as technical production limitations (Böhringer, Löschel, & Rutherford, 2004). In this way, the models optimize at the macroeconomic level and assume utility-maximizing and representative individuals, complete markets without external effects and public goods, complete information, perfect competition, etc. CGE models often examine macroeconomic issues, which today typically have an empirical background (Böhringer et al., 2004). By limiting the market outcome to economic equilibrium, their results are limited from an empirical perspective – particularly in non-Walrasian market situations. However, recent CGE models allow deviation from the equilibrium (e.g. Sampson, 2013). Calibrating the model is still a challenge and is mainly based on values from the literature or estimated by econometric approaches and confirmed by a sensitivity analysis (Boulangier & Bréchet, 2002). If correctly calibrated, CGE models are especially suited to determining long-term forecasts.

#### *Literature*

In the context of market penetration of electric vehicles, only few CGE-based studies exist. Most models apply the rather theoretical constant elasticity-of-substitution (CES) approach to all drivetrain technologies (e.g. Karplus, Paltsev, & Reilly, 2010), whereas also other methodologies are applied, e.g. a hard-linked MNL (cf. Table 9). A comprehensive overview of IAM for vehicle choice can be found in McCollum et al. (2016).

Table 9: Overview of literature on market penetration of electric vehicles based on general equilibrium models

Authors	Jurisdiction	Time horizon	Technology	Key features
Schäfer and Jacoby, 2006	US	2030	Different technological improvements	The MARKAL model is linked to the EPPA (emission production and policy analysis) model in order to consider also influences from the economy. Eight technology improvements for conventional cars are considered, including hybridization.
Schmelzer and Miess, 2015	Austria	2030	EV, PHEV	A hard-linked MNL model is used for the technology choice of households instead of the usual constant-elasticity-of-substitution (CES) approach. The authors even consider spatial differences.
Karplus et al., 2010	US and Japan	2100	Biofuels, PHEV	The alternative technology PHEV is considered as a perfect substitute of conventional vehicles in the EPPA model. Biofuels are also considered as an alternative to electrification. The choice between the perfect substitutes is based on a usual constant-elasticity-of-substitution (CES) approach.
Yeh et al., 2008	US	2050	PHEV	A MARKAL model based on Shay et al. (2006) is applied, and the technology decision remains unclear.

### Discussion

General equilibrium models have a strong theoretical basis from economic theory and lead to unique results – especially for long-term scenarios. This comes, however, along with some drawbacks such as that the (mostly) simplifying assumptions of user behavior might not represent reality of car purchase decisions and disruptive innovations are hard to capture (cf. Table 10).

Table 10: Advantages and disadvantages of integrated assessment and general equilibrium models

ADVANTAGES	DISADVANTAGES
<ul style="list-style-type: none"> <li>• CGE: Strong <u>theoretical basis</u>.</li> <li>• CGE: Comprehensive structural view of the economy.</li> <li>• IAM/CGE: Consistent scenarios of <u>long time horizons</u> possible.</li> <li>• CGE: <u>Unique solution</u>.</li> </ul>	<ul style="list-style-type: none"> <li>• IAM: Weak theoretical basis.</li> <li>• CGE: Rational expectations assumption arguably unrealistic.</li> <li>• IAM: Due to a <u>weak theoretical background</u> it is hard to follow all assumptions.</li> <li>• CGE: Simplifying assumptions required to make the model tractable.</li> <li>• CGE: Nonlinearities are hard to capture.</li> </ul>

	<ul style="list-style-type: none"><li>• There is no standardized toolbox available yet.</li></ul>
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## 5 Hybrid Models

Hybrid models (i.e. models, which use bottom-up and top-down approaches) are more and more recommended in academia for analyzing the market share of alternative drivetrains in order to consider both, the individual decision, as well as the overriding trend in society and the vehicle supply (Brand, Anable, & Tran, 2013; Brand, Tran, & Anable, 2012; Jensen et al., 2016; Kieckhäfer et al., 2014; Wansart, 2012; Weikl, 2010). Furthermore, these hybrid models are already broadly applied in comprehensive long-term global models developed by policy consultants: E.g., the data spread sheet models Mobility Model (MoMo by the International Energy Agency (IEA)) (Fulton, Cazzola, & Cuenot, 2009) and the Roadmap Model (by the International Council on Clean Transportation (ICCT)) as well as the system dynamic-based ForFITS model (by United Nation Economic Commission for Europe). In addition, in European policy consulting, several hybrid models are developed such as ASTRA, POLES, TRANS-TOOLS (TOOLS for TRansport Forecasting ANd Scenario testing) and REMOVE.

In academia, these hybrid approaches are, however, still underrepresented even though new convincing developments are proposed e.g., by Zhang and Vorobeychik (2016), who suggested to integrate more machine learning algorithms, which consider both macro-level and micro-level such as cross-validation, or validate the models with independent data, which is not used for model calibration. Application of these methods is based on the availability of comprehensive data sets. The current tremendous increase in data volumes from transportation will contribute to an improvement of these models. Future data is not only based on mobility data, but also comes from other sources such as social media (Rand, Herrmann, Schein, & Vodopivec, 2015). This might lead to a more data-driven approach in our field of investigation.

## 6 Discussion

There is a high variety of methods applied in the literature for forecasting the market penetration of electric drivetrains in the passenger car market. There is no dominating methodology, but it seems that each method has its advantage in certain fields.

Nevertheless, we indicate the strength and weakness of each method according to four main dimensions (1) main basis (theoretically vs. empirically), (2) transparency and (3) flexibility of modelling as well as (4) appropriate time horizon (short-term vs. long-term) in Figure 3.

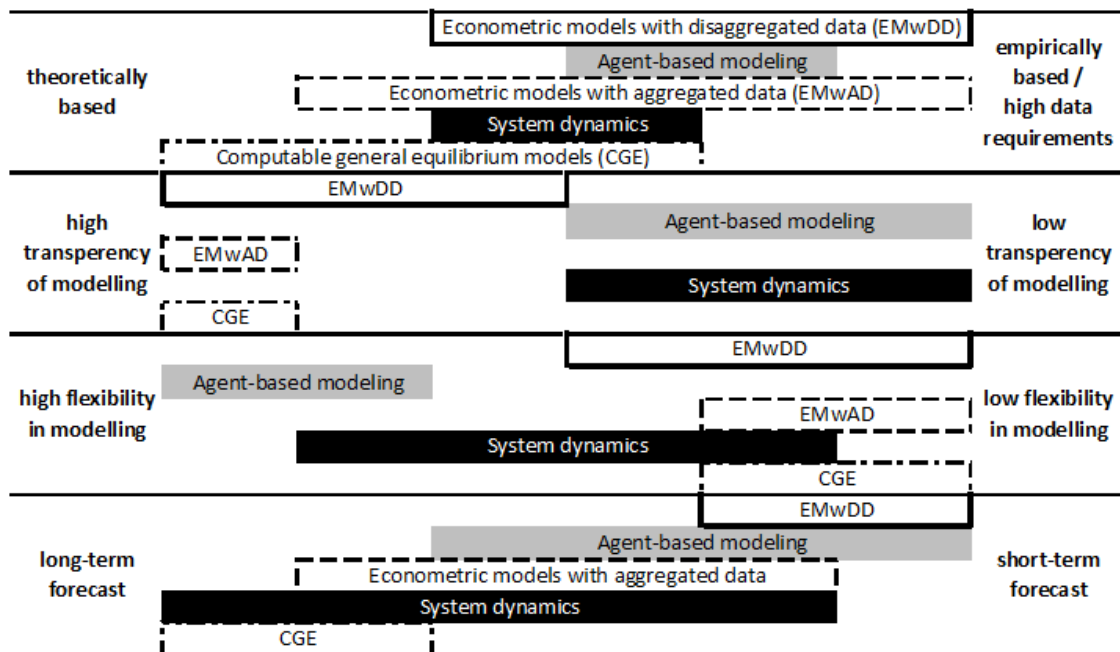


Figure 3: Evaluation of modeling approaches according to four dimensions

The theoretical basis seems to be strong for both CGE and econometric approaches, which convince for stable market conditions. However, the strong theoretical basis makes some methodological applications more unrealistic (e.g. theoretical CGE models). A weak theoretical basis leads on the one hand to less transparency of modeling which comes along with a limited reproducibility and on the other hand to a high degree of freedom for model developers. Hence, econometric modeling convinces strongly with a profound theoretical basis without neglecting

empirical soundness and high transparency of modeling, but requires a comprehensive database.

Another main dimension, where applied methodologies perform differently is the flexibility of modeling, where ABM and SD perform best. However a high flexibility is often correlated with a low transparency in modeling. Finally, pure econometric approaches are rather focused on short- to mid-term forecasts. For long-term forecasts, CGE and SD models perform best.

A combination of pure modeling techniques such as CGE, SD or AGM with econometric methods seems to be a promising combination of measuring the empirical historical development, using expert insights about the future and using the existing theoretical basis of modeling.

For early market phases, especially disaggregated econometric bottom-up models seem to be appropriate to generate an adequate basis for market prognoses. However, these econometric models are highly relying on comprehensive data which comes along with high costs of data collection. While data collected from user acceptance studies can be used for past or present decisions, the stated preferences on future decisions should be handled more carefully.

If disaggregated data is available and a concrete car purchase decision is in the core of the specific research question (mainly perspective of the car industry) and the focus is on the short- to mid-term development, ABM and econometric based models with disaggregated data seem favorable. For long-term forecasts (mainly perspective of politics), macroeconomic based models, mainly CGE and SD, seem to be more appropriate. Due to the relatively new market development of this technology, a pure application of econometric models with aggregated data cannot convince in our research area.

Finally, the market penetration of electric drivetrains depends on the car purchase decision of the main three customer sub-groups, i.e. (1) companies buying fleet vehicles for their fleets, (2) companies buying company cars for their employees, and (3) private persons buying cars for themselves or other family members. All three customer groups react differently and even within a group significant differences might be observed (de Haan et al., 2009; Gnann et al., 2015; Ketelaer, Kaschub, Jochem, & Fichtner, 2014). However, all decision makers consider (at least implicitly) the following decision factors:

- Personal beliefs and attitudes (micro-level), such as innovativeness, environmental attitudes, preferences for different makes, vehicle types, etc., which can be influenced by macro-level factors such as media or politics,
- budget and phase of life (micro-level), all decision makers usually have budget restrictions, and private customers take their current phases of life into consideration (e.g. retirement, etc.),
- mobility patterns (micro-level), refer mainly to annual mileage, but also to daily patterns, which might be restricted by the range of some cars,
- external factors (macro-level), such as political influences (i.e. incentives), fuel prices, availability of fueling stations, etc.,
- other factors (mainly macro-level), which include all other influences.

Concluding, future models should consider the macro- and micro-levels by all five decision factors differentiated by the three sub-groups, fleet vehicles, company cars, and private cars. For this, a comprehensive collection of economic, market and social data is necessary.

As there has been no market penetration of a similar technology and the current market uptake of electric vehicles is still at a very early stage, it will take time to fully validate the model results. Nevertheless, methods from other markets and the increasing volume of mobility data provide promising improvements in our research field.

## **7 Conclusion**

In this paper, we analyze different methods for forecasting the market penetration of electric drivetrains in the passenger car market in order to structure them and highlight their strengths and weaknesses. We classify the methods into bottom-up and top-down models. For the former, we identify microeconomic models and agent-based simulation models, which focus on representing the user decision. Econometric models with aggregated data, system dynamics, and integrated assessment models with general equilibrium models are classified in the top-down models. As a trend in the literature already indicates, hybrid approaches, considering micro and macro aspects seem to be most appropriate for analyzing the market penetration of electric drivetrains in the passenger car market. This is a consequential conclusion from the finding that not only personal beliefs (bottom-up effect) influence our car purchase decision, but also other social, economic and political factors (top-down effect). Furthermore, the differentiation between the three sub-groups, fleet vehicles, company cars, and private cars combined with suitable methods should be included in future models. The current increase in data volumes from transportation will contribute to this development.

The literature in this research field has been gaining momentum in the last years. Therefore, we may be far from giving a complete overview of the research field. Our argumentation is focused on our research question and may seem inappropriate for other fields of application.



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