Dynamic modeling of vehicle purchases and vehicle type choices from national household travel survey data

Francisco J. Bahamonde-Birke*, Benjamin Kickhöfer, Falko Nordenholz, Lars Kröger

Institute of Transport Research

German Aerospace Center (DLR)

*Correspondence address: bahamondebirke@gmail.com; francisco.bahamonde@dlr.de

Extended Abstract

The information about car availability and usage is crucial for transportation models as car ownership deeply influences all levels of travel behavior (i.e. trip generation, destination and mode choice). Thus, modeling vehicle purchase decision accurately is a key factor for transport planning and policy setting.

While several studies have addressed the drivers triggering the purchases of new vehicles (e.g. Bahamonde-Birke and Hanappi, 2016; Fernández-Antolín, 2016), models aiming at depicting the entire vehicle fleet are scarce. In the literature, – apart from aggregated models, which predict the total number of vehicles in a country as a function of aggregated variables, such as the GDP – there exist disaggregated models. These models can be differentiated by their respective approach[1]: (i) static vehicle holding/ownership (and use) models, and (ii) dynamic vehicle transaction (and use) models. The former aim at predicting, for a given point in time, the discrete number of vehicles owned by a household as a function of the explanatory variables. Nonetheless, their goal is not to replicate the dynamics involved in the vehicle purchase/selling decisions. Therefore, they are only appropriate to model end-state conditions and fail to replicate the impact of changing exogenous conditions and/or policy measures that have a continuous impact over time. Thus, it is not possible to rely on these models to evaluate the impacts of a given policy in the transition phase, i.e. before the system reaches the modeled stationary state.

In contrast, dynamic vehicle transaction models focus on vehicle transactions over time, by modeling explicitly the decision of purchasing, selling or keeping a given vehicle, over the course of several time cycles (Mohammadian and Miller, 2003). Some of these models try to link the decisions to so-called life-course events, such as the birth of a child, residential relocation, or a change in employment status (e.g., Yamamoto, 2008; Chen et al, 2013; Fatmi and Habib, 2017). These models were often criticized as too data-intensive as they are usually built on panel data, which in many cases do not exist (Bunch et al., 1995; Bhat and Sen, 2006). De Jong et al. (2004) argue that static models are reasonable approximations to forecast long-term equilibria, i.e. that a change in the

[1] For a comprehensive review of car ownership models and a more detailed classification, please refer to de Jong et al. (2004).

explanatory variables will eventually lead to the expected system state. However, in markets with long replacement times (the average age of passenger cars in Germany is 8.47 years with increasing tendency; Follmer et al., 2010), this argument of long-term convergence becomes weak. Also Pendyala et al. (1995) question the existence of such equilibrium points since elasticities are found to change over time. Hence, dynamic models are needed to capture the transition phase, especially in situations where major disruptions in the mobility market are expected.

Therefore, we are building a dynamic vehicle transaction model, similar to the one by Mohammadian and Miller (2003). This paper presents the first step necessary to build such a model establishing the preferences of the individuals as well as the behavioral decision rules to be implemented into the model. For this purpose we estimate several discrete choice models to depict the behavior of individuals in the vehicle purchase market. However, and in contrast to Mohammadian and Miller (2003), the behavioral models are not estimated on the basis of panel data, but rely on national household travel survey data only. This also comes with some limitations, but the main advantage of this approach is the better availability of the data. We address the limitations and hypotheses imposed through the use of cross-sectional data.

Furthermore, our approach, differs from the model by Mohammadian and Miller (2003), as the special characteristics of German vehicle market require considering its particularities. In Germany, given the tax incentives in place, a large proportion of vehicles used for private purposes are user-chooser company vehicles, which are part of the employee's remuneration.[2] These vehicles represent 27% of new vehicles sales, while actual private purchases represent 46%, and the remaining vehicles are part of company fleets[3]. Because of the aforementioned tax reasons, the replacement times of these user-chooser company vehicles are considerably shorter than for the other vehicles. As a consequence, Germany has a very vibrant used vehicle market; it represents 60% of the total vehicle transactions. As the market characteristics of new user-chooser company vehicles, new private vehicles, and used vehicles differ, also the user preferences in those markets are likely to vary. Hence, it is necessary to recognize the differences among them and to estimate different behavioral models.

In a first step, we establish the likelihood of a household being active (purchase and disposal probabilities) in the used vehicle, new vehicle, and new user-chooser company vehicle (mainly used for private purposes) markets. Furthermore, as we are considering used vehicle market, it is necessary to establish in which segment of this market the households are likely to hold, as used vehicles exhibit a large variability in terms of age, mileage and price. Finally, we consider vehicle type choices for the attributes powertrain (diesel vs gasoline) and size class (small, medium, large). This model lays the foundations for integrating alternative powertrains and automatization levels later on, planned to be integrated by linking the discrete choice to a diffusion model. Summarizing, our model considers three different decision in an integrated fashion: vehicle market, segment (provided the vehicle market is the used vehicle market), and vehicle type.

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[2] Private use of a vehicle owned by the employer may reduce an employee's income tax due to German tax regulations and, hence, might be less expensive than a privately owned vehicle.

[3] Own calculations based on KBA (2017a, 2017b) and Plötz, Gnann et al. (2013).

A simultaneous treatment of the three choices would require addressing 31 alternatives: three different vehicle markets, three segments in the used vehicle market, three different size classes, two different powertrains, and one non-purchase alternative. It is therefore computationally highly expensive to consider a full correlation matrix at all decision levels in a simultaneous estimation, also giving the high number of observations (25,922). Therefore the model is estimated in three steps addressing first the vehicle market, then the used vehicle market segment and the type-choice decision (size class and powertrain) independently. It is assumed that the type-choice decision is subordinated to the vehicle market and the used vehicle market segment decisions. The vehicle market decision, including the non-purchase decision, as well as the type choice decision are modeled making use of a fully-correlated heteroscedastic Mixed Logit model (Walker et al. 2007). The used vehicle market segment decisions is modeled on the basis of an Ordered Logit (OL) model.

The basis of the proposed model is the national household travel survey “Mobilität in Deutschland 2008” (MiD 2008, see Follmer et al., 2010). It has been undertaken between March 2008 and May 2009. Currently, it is the most recent comprehensive survey with information on vehicle purchase/ownership, but an update of this comprehensive study is expected for mid-2018. It consists of 25,922 households with 34,601 vehicles; 4,043 of these vehicles were recorded as purchases by 3,780 households in the year 2007, the last fully covered year before the survey.[4] After omitting vehicles with unknown registration type (e.g. held privately or by a company), this results in 3,166 vehicle transactions with 1,699 cases of used vehicles, 414 cases of new user-chooser company vehicles, and 1,053 cases of new private vehicles.

The results of the estimation indicate that a heteroscedastic cross-nested structure is needed to capture the correlation between the different vehicle markets. We identify a strong correlation among all purchase decisions, private transactions in general, and the purchase of new vehicles (private and user-chooser company vehicles). Furthermore, we find statistically significant effects in association with living in rural or urban areas, number of driver’s licenses, income, number of employed household members and the number of vehicles available at the time (as well as with the characteristics of the markets in itself). The same attributes are found to be statistically significant in the OL used to model the used vehicle market segment. Finally, regarding the type-choice model, we identify a strong correlation across size-classes but not across power trains. We also identify a strong negative utility associated with price and energy consumption of the vehicles.

Keywords: Vehicle ownership, vehicle purchase, vehicle type choice, national household travel survey

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[4] Presumably, some of the vehicles purchased in 2007 might already be sold again at the time of the interview; however, we assume this number to be small enough to not have a significant structural impact on the results.

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