BABEȘ-BOLYAI UNIVERSITY CLUJ-NAPOCA

DOCTORAL SCHOOL OF ECONOMICS AND BUSINESS ADMINISTRATION

Ph.D. THESIS

SUMMARY

DEMAND AND WELFARE ANALYSIS OF ENVIRONMENTALLY FRIENDLY PRODUCTS: THE CASE OF THE HUNGARIAN ELECTRIC CAR MARKET

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Keywords

battery electric vehicles, demand, welfare, random coefficients logit, government subsidy, pricing, nash equilibrium, spatial effects, charging infrastructure, socio-demographic factors.

1. Introduction

This thesis is a collection of research studies on demand for environmentally friendly products, namely battery electric vehicles (BEVs), on the Hungarian market. These studies consist of two main research topics. The first topic is based on spatial econometric models and studies how sociodemographic and economic factors influence the spread of BEVs. The second topic is based on discrete choice models and studies two different aspects of the Hungarian BEV market, namely estimation of the demand side and pricing.

First, the noteworthiness of local-specific attributes is highlighted in the literature, which maintains high applicability from the perspective of policy makers (Morton et al., 2018). Furthermore, with increasing demand for electric vehicles, it is important to understand the spatial patterns of EV adoption to minimize the risks associated with the spatial accumulation of EV drivers (Zhang et al., 2023; Jenn et al., 2018), the possible positive or negative neighborhood effects of sociodemographic and economic factors (Morton et al., 2018; Egbue and Long, 2012; Liu et al., 2017; Sheng et al., 2023; He et al., 2022; Gehrke and Reardon, 2022; Zhuge and Shao, 2019; Mukherjee and Ryan, 2020; Yang et al., 2023), and the level of efficiency in the distribution of government subsidies (Jenn et al., 2018; Guo and Kontou, 2021; Haan et al., 2023). In addition, numerous research articles examine the spatial effects of charging stations (Westin et al., 2018; Schulz and Rode, 2022; Yang et al., 2023; Sheng et al., 2023).

As price is an important factor in the purchasing decision, the second main driver to stimulate the spread of fuel-efficient vehicles are various forms of government incentives (Clinton and Steinberg, 2019). Therefore, governments started to invest and provide several types of subsidies and tax reductions to promote the fast spread of electric vehicles. Diamond (1967) was the first to formulate the main issue that leads to welfare losses in the case of government subsidies. This welfare loss, which is typically a reduction in the consumer surplus, results from the fact that producers tend to partially implement the value of the subsidy in their final price, thus increasing the producer surplus. The literature is rich in analyzing the efficiency of government incentives (see for example Sallee, 2011; Beresteanu and Li, 2011; Xiao and Ju, 2014; Yang and Tang, 2019); however, only a few research articles focus on the issue described by Diamond (1967). Diamond (2009) is one of the first articles to study the impact of government subsidies on the adoption of hybrid electric vehicles (HEVs) and concludes that the relationship between them is very weak, probably due to uncontrolled subsidy eligibility and therefore a potential increase in prices. This is followed by several investigations on how subsidies can be designed to overcome or at least reduce the effect of this phenomenon (see for example DeShazo et al., 2017; Haan et al., 2023; Fan and Zhang, 2022; Barwick et al., 2024). In summary, we learn from the literature that government subsidies are effective, especially if combined with the large availability of charging stations (Zhuge and Shao, 2019); however, increasing efficiency by targeting the right consumer group (Gallagher and Muehlegger, 2011; Sheldon and Dua, 2019, 2020; Guo and Kontou, 2021; Haan et al., 2023) and preventing firms from capturing benefits of the subsidy (Fan and Zhang, 2022) are equally crucial.

As spatial autocorrelation tests regarding cross-county relationships revealed a positive and significant effect on BEV registrations, spatial modeling is required. In this thesis, spatial analysis is conducted in two phases; first, a spatial analysis of cross-sectional data is performed for the year 2022, followed by a spatial panel analysis from 2015 to 2022. Therefore, the process of model selection is presented for both cross-sectional and panel data. Finally, the direct and indirect (or spillover) effects of specific spatial models are elaborated.

The second research topic of this thesis uses discrete choice models, specifically the model developed by Berry, Levinsohn and Pakes (henceforth, BLP) in their renowned article Berry et al. (1995). The estimation method of the BLP demand model, extended with an estimation approach of the model using regional sales, is presented. This extension of the estimation process is useful as the number of observations for BEV sales is somewhat low.

The price-contingent subsidy design presented in Chapter 2 plays an important role on the supply side. Considering the Nash-Bertrand competition game, in case of no price cap a Nash equilibrium usually exists and profit-maximizing prices can be calculated for counterfactual analysis. In a case of a subsidy with an eligibility price cap, however, since profit functions are not continuous, a Nash equilibrium may not exist and its calculation is difficult. This part of the thesis seeks to make one step further in understanding better the pricing problem.

2. Background and Data

The background of this thesis is based on a specific price-contingent subsidy program having a structural design, which implies an eligibility price cap beyond that vehicles do not qualify for subsidy. Aggregate registration data come from a Hungarian company called 'DATAHOUSE', which collects and processes data on new cars registered in Hungary. The source of the data is the sales input database provided by Hungarian new car importers. The database contains information on Hungarian new BEV sales between the 2016 and 2022 time period and includes the following characteristics of cars: make, model, model year, doors, body type, seats, kW power, size, list prices (net and gross), list price with dealer discounts, amount of subsidy (if applicable), sales year, sales month, registration county, and number of units sold. Additional information, such as range, battery capacity, charging time, maximum speed, and consumption, is collected from the online 'Electric Vehicle Database', available at: https://ev-database.org/. Data on the number and type of publicly available charging stations are collected from the Hungarian Energy and Public Utility Regulatory Authority and from the Hungarian Ministry of Innovation and Technology. These data are available from 2015 to 2022 and contain information on the number of piles, the number of connectors, the maximum capacity, and the type of charging stations at the county level. Finally, data on sociodemographic and economic variables are gathered from the official Hungarian Statistical Office. These data are used for spatial analysis and contain information on population size, average income, urbanization level, number of vehicles, number of university students, and the number of inhabitants per household from 2018 to 2022 at the county level.

3. Spatial Analysis

As spatial autocorrelation tests regarding cross-county relationships revealed a positive and significant effect on BEV registrations, spatial modeling is required. n this thesis, spatial analysis is conducted in two phases; first, a spatial analysis of cross-sectional data is performed for the year 2022, followed by a spatial panel analysis from 2015 to 2022. Therefore, the process of model selection is presented for both cross-sectional and panel data. Finally, the direct and indirect (or spillover) effects of specific spatial models are elaborated.

First, the results based on cross-sectional data for 2022 show that early adopters are mostly high-income consumers living in urban areas and that a higher average income value in one county is followed by an increase in the number of new BEV registrations in surrounding counties. Furthermore, we show that the distribution of the fast charger is the only variable that explains the adoption rate of the BEV without considering spatial effects.

The results based on panel data are pointing in similar directions; however, in this model the percentage of persons living in urban areas was not significant. On the other hand, the results of the spatial analysis based on both cross-sectional and panel data analysis confirm that income has a positive and significant effect on BEV uptake. This is in line with previous spatial research results highlighted in the literature. For example, Gehrke and Reardon (2022), who show that early uptake of electric vehicles is distributed to wealthier and single households, Yang et al. (2023) who show that increasing median household income by approximately 11,000 USD, the adoption rate of BEVs increases by 26.3% or Jia and Chen (2021) who show, both based on survey data and registration data, that less wealthy households are more sensitive to price in the decision-making process of BEV purchase.

Similarly, the distribution of fast-chargers and the number of fast-charging connectors have a positive and significant effect on the new BEV registrations in our empirical research and the literature. Some examples from the literature are Yang et al. (2023), who show that an increase in the number of public charging stations by 100 units results in an increase of 2.9% in the adoption rate of BEVs, Schulz and Rode (2022), who show that the installation of public chargers is followed in five years by a spread of more than 200% in electric vehicles, Illmann and Kluge (2020), who show that the speed of charging influences the adoption of electric vehicles more than the number of charging stations, or Haustein et al. (2021), who precisely suggest the expansion of the fast-charging network. Lastly, Jia and Chen (2021) show both in survey and registration data that the availability of fast chargers has a positive and significant effect on BEV registrations.

The level of education in this study was captured by the number of people enrolled in a university. A similar method was used by Mukherjee and Ryan (2020), who found a significant positive effect of education on BEV adoption, and by Brückmann et al. (2021), who also found a positive but insignificant effect of the variable. The level of education is also significant and positive in the studies of Westin et al. (2018); Jia and Chen (2021); Morton et al. (2018).

The average number of vehicles owned by a household raises some additional questions as it has a significant positive effect in the study by Sheng et al. (2023) and a significant negative effect in the study by Zhang et al. (2011), who points out that the increase in the number of cars owned by a household has a negative effect on the purchase of electric vehicles; however, wealthy families own more cars and, as income is positively associated with the adoption of EVs, the number of cars owned can have a positive effect on the adoption of BEVs. The results of the spatial panel analysis show a positive significant effect of the avergae number of vehicles owned by a household on the new BEV registrations, but it should be noted that this effect might be a result of the presented association.

Finally, the three insignificant variables are discussed. The percentage of people living in urban areas has a weak, but positive and significant (at the 10% significance level) total effect in the cross-sectional analysis; however, it is not significant in the panel analysis. Age was included only in the panel analysis, where it had a positive and significant effect in the pooled OLS model, but an insignificant negative effect in the spatial panel fixed effects SAR model. Age also has a controversial status in the literature, as, for example, Yang et al. (2023) and Westin et al. (2018) found that the younger population has a positive and significant effect on the BEV adoption, while Mukherjee and Ryan (2020) found a significant negative effect of the same variable. Jia and Chen (2021) also found controversial results considering age in the survey- vs. registration-based data analysis. Finally, in the study conducted by Brückmann et al. (2021), the age is not significant. Lastly, similar to Brückmann et al. (2021), gender is also insignificant in our analysis, while it demonstrated significant effects in studies conducted by Jia and Chen (2021); Sheng et al. (2023), who found a positive association between being male and purchasing BEVs.

These results can be valuable to decision makers and policy makers in identifying areas that may require attention or intervention in terms of infrastructure development, resource allocation, or policy implementation to address disparities in access to charging infrastructure or subsidy programs targeted to disadvantages areas.

Considering the methodology, we used the SLX model for cross-sectional analysis and the spatial panel fixed effects lag model for panel analysis. Both models have been criticized in the literature. First, Gibbons and Overman (2012) criticize the SAR, SEM, and SDM models for identification reasons and advocate the SLX model. However, based on the work of Elhorst (2014), the SDM outperforms the SLX model. Similarly, SDEM appears to be better than the SEM and SLX models Elhorst (2014). As the LM test showed significant spatial lag dependence in the data, we first estimated the SDM model for cross-sectional data and the fixed effects SDM model for panel data. However, the spatial autocorrelation coefficient (ρ) did not prove to be significant in either case. Our future research will focus on the identification of this issue based on two approaches that have been developed and are promising. The first is developed by LeSage (2014) and is based on Bayesian comparison methods, and the second is developed by Halleck Vega and Elhorst (2015) and is based on taking the SLX model as the point of departure instead of the OLS linear regressions. In addition, future research could improve this work by estimating these models based on data gathered from more emerging markets.

4. Discrete Choice Models

The pricing game analysis is based on a price-contingent subsidy program, which implies an eligibility price cap beyond that vehicles do not qualify for subsidy. In case of such subsidy design, profit functions are not continuous and a Nash equilibrium may not exist. This thesis seeks to make one step further in understanding better the pricing problem. We show that in a one-product monopoly we can distinguish three profit-maximizing prices based on three distinct price intervals, each profit-maximizing price corresponding to a different price cap set within those intervals

4.1 Demand

The second research topic starts with the estimation of a random-coefficients logit demand model. We construct an estimator based on regional sales data, as such an estimator avoids many of the problems related to instruments. The estimated coefficients of car characteristics are in accordance with expectations, as the price variable affects negatively, whereas the power, size and range variables affect positively the demand. As estimates are in accordance with expectations, there is great potential in future research considering this model and its estimation provided. It should be noted that these results are only preliminary, however as they are in accordance with expectations they validate the model despite the quite low number of disposable observations. Therefore this model is of great importance for future counterfactual analysis examining the efficiency of the subsidy design with eligibility price caps.

4.2 Supply

The supply side of the random coefficients logit model is crucial to calculate profit-maximizing prices. Following BLP (Berry et al., 1995), it is usually assumed that firms engage in price competition under Nash equilibrium, leading to a non-linear system of equations for the profit-maximizing prices. However, in the context of our research, this standard method does not apply, as firms are facing a price-contingent subsidy.

Usually it is assumed that there are F firms, $f \in \{1, ..., F\}$ and they solve a standard Bertrand price competition game, thus one firm sets its prices given other firms' prices, so we denote the prices of competitor firms' products by p_{-f} and the marginal cost of product j by mc_j. We denote the product set of firm f by $\mathcal{J}_f$. The profit of firm f is defined as follows:

$$\pi_f(p) = M \sum_{j \in \mathcal{J}_f} (p_j - mc_j) s_j(p_f, -p_f) \tag{4.2.1}$$

where p is the vector of all prices and M is the number of consumers. For notation purposes we denote the market share function as $s_j(p_f, -p_f)$. The Nash equilibrium is given by the solution p^* of the non-linear system of equations:

$$\frac{\partial \pi_f}{\partial p_j}(p) = 0, f = 1, ..., F, \tag{4.2.2}$$

which is equivalent to:

$$s_j(p) + \sum (p_r - mc_r) \frac{\partial s_r}{\partial p_j}(p) = 0 \tag{4.2.3}$$

It is important to note that such a Nash equilibrium of prices exists and is unique in most cases. Conditions for existence are provided by Caplin and Nalebuff (1991) in the single-product firms case that covers the (normally distributed) random coefficients logit demand and by Konovalov and Sándor (2010) in the multi-product firms case for the standard logit, where the equilibrium is also shown to be unique.

Following Barwick et al. (2024), we consider a single product monopoly that analyzes the behavior of profit functions with imposed eligibility price caps above which products are not eligible for the subsidy. The analysis is performed through graphical representation of the profit functions in four scenarios that have distinct profit-maximizing price outcomes, due to differently defined setups of price caps and subsidy amount values.

We show that in a one-product monopoly we can distinguish three profit-maximizing prices based on three distinct price intervals, each profit-maximizing price corresponding to a different price cap set within those intervals. Two of the profit-maximizing prices are fix values, the first value being the profit-maximizing price in case no subsidy is available, the second being the profit-maximizing price in case a subsidy without eligibility price cap is available. The third value is the value of the price cap itself and can take any value within the interval where the profit-maximizing price equals the price cap. The two fix profit-maximizing prices are the result of a standard Nash-Bertrand competition game as they derive from functions which on the relevant intervals are continuous, whereas the third profit-maximizing price is always at the break-point of the profit function.

5. Conclusions

The aim of this thesis was to provide an in-depth demand and welfare analysis on the BEV market in Hungary. For this two different research topics were studied. First, results on spatial analysis are presented, starting with the cross-sectional spatial analysis that is followed by the results of the spatial panel analysis. The results for the second research topic begin with the presentation of estimates from both the standard logit and random coefficients logit demand models. This is followed by a contribution to methodology on the supply side, provided by a theoretical approach for the calculation of profit-maximizing prices in the context of a price-contingent subsidy on a one-product monopoly market. Finally,this approach is applied to three selected BEV models, for which the main results are elaborated.

Moran I's spatial autocorrelation tests show significant spatial autocorrelation in the new BEV registrations across counties in Hungary for all years analyzed. Estimation results of the spatial model based on cross-sectional data from 2022 reveal that early adopters are predominantly high-income consumers residing in urban areas. Additionally, higher average income in a county correlates with an increase in new BEV registrations in neighboring counties. Furthermore, the analysis shows that the distribution of fast chargers is the sole variable explaining the BEV adoption rate when spatial effects are not considered.

The results based on panel data point in similar directions; however, in this model, the percentage of people living in urban areas was not significant. On the other hand, spatial panel analysis confirms that income has a positive and significant effect on BEV uptake. Furthermore, in the spatial panel analysis, the level of education, measured by university enrollment, was also positive and significant, aligning with existing literature.

Additionally, results reveal a positive and significant effect of the average number of vehicles owned by a household on new BEV registrations, which contrasts with some findings in the literature. Note that in this specific literature contrasting results are not uncommon, which are mainly due to the fact that the majority of studies rely on stated preference survey data. The primary advantage of the spatial research conducted in this thesis is its exclusive reliance on registration data, thus contributing to the literature by providing data-driven insights from an emerging country.

Comparing the results of the standard logit and random coefficients logit demand models, we see that the statistical significances are substantially higher in the latter one, suggesting that regional sales and income distributions carry useful information about demand for electric cars.

In summary, results show that consumers prefer larger, more powerful cars with higher range that are less expensive. These results are only preliminary, as a better estimation could be performed using more random coefficients. However, as the estimates are in accordance with expectations, there is great potential in future research considering this model and its estimation provided using regional sales. Therefore, the presented estimation of the random coefficients demand model, together with the analysis of the supply side, constitute a good starting point for future research to estimate the supply side and conduct counterfactual analysis that examines the efficiency of the subsidy design dependent on the price-cap value set.

The calculation of profit-maximizing prices, needed for counterfactual analysis in future research, on the supply side in the context of a price-contingent subsidy contributes to the methodology considering Nash-equilibrium points in specific frameworks. To the best of our knowledge, within the price-contingent subsidy framework discussed in this thesis there may exist no Nash equilibrium for prices in an Oligopoly market structure with differentiated products. Therefore, we assumed a one-product monopoly market structure, where we show that profit functions are not continuous but have a break-point at the value of the price cap. In this market structure we show that the profit-maximizing price can take up only three values: the profit-maximizing price without any available subsidy, the profit-maximizing price with subsidy, but no price cap for eligibility and the value of the price cap (just below it). In addition, we also show that there are exactly four price-cap intervals, each of which generate one of these three profit-maximizing prices that can be calculated.

In addition to calculation of the profit-maximizing prices, a valuable aspect of our model is that it can be used to conduct welfare analysis. We show that if the price set by a one-product monopoly is not equal to the price cap, the consumer could have been in a better setting if the price cap value chosen by the government would had been set in the interval where the profit-maximizing price equals the price cap. More than that, we also demonstrate that the value of the subsidy is fully captured by the consumer if the price set by the firm is between the indifference point and the profit-maximizing price without subsidy. Also, the firm never fully captures the subsidy value, however, it gains a share of it (that can be calculated) if the price cap is set higher than the profit-maximizing price without subsidy.

It should be noted, that the approach provided has some limitations, such as the assumption of a one-product monopoly market structure. However, as in an oligopoly market structure a Nash-equilibrium may not exist, the results of the one-product monopoly may be conceptually useful in cases of more firms and products as well. In addition, this approach may represent a good point of departure for future research aiming to find the profit-maximizing prices under less restrictive conditions.

Using our approach on new registration data, we show that the eligibility price cap in the first two cycles was set too high and had a price-increasing effect on the Hungarian BEV market. In addition, for three selected BEV models, we show that the eligibility price cap was set in the optimal price interval in the third cycle of the subsidy, as both the observed and the calculated profit-maximizing prices were just below the eligibility price cap. We also see from the data, that in the case of the analyzed BEV models, the lowest prices were set and the highest sales were made in this cycle of the subsidy.

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