Socioeconomic Determinants of Electric Vehicle Adoption in Czechia

Jindra Lacko [1]

Abstract. In an effort to reduce transportation-related CO_2 emissions to levels below those of 1990, the European Union and the Czech Republic are prioritizing the transition from internal combustion engines to battery-operated and hybrid propulsion vehicles. This study examines Czech vehicle registration data in the retail sector from 2019 to 2022, utilizing a stepwise linear regression approach to develop a model that explains the rate of electric vehicle adoption based on 37 socioeconomic predictors across 206 Czech administrative regions. The resulting model identifies five significant predictors, demonstrates a robust goodness of fit, and effectively mitigates the spatial autocorrelation initially observed in the data.

Keywords: Battery electric vehicles, Hybrid vehicles, Technology adoption and diffusion, Czechia

JEL Classification: Q54, C31
AMS Classification: 62M30

1 Introduction

Reducing CO_2 emissions significantly in comparison to 1990 levels is a target of both global [1] and regional initiatives [2]. A key factor for achieving this aim is reducing the volume of CO_2 emissions from transportation. This is in line with the contribution transportation related emissions have made to the current stock of CO_2 in the Earth's atmosphere. In order to achieve these aims it will be necessary to significantly reduce the volume of active Internal Combustion Engine (ICE) vehicles on EU roads. While alternatives to personal vehicle ownership such as mass transit and bicycling are certain to be a part of the solution it is unlikely that the current level of vehicle ownership (over 6 million personal vehicles are registered in the Czech Republic alone, a country of 10 million inhabitants [3]) could be feasibly reduced to zero.

As a consequence any plan to reduce and / or eliminate ICE personal vehicle ownership and use must include introducing of alternatives, such as Electric Vehicles (EV's). A number of studies was performed to evaluate the effectiveness of incentives in reducing ICE and promoting EV vehicle ownership. These were mostly focused on United States [4], [5]. In the European context important data come from Norway (global leader in EV adoption) [6], [7]. In Central Europe a review was performed of Polish customer preferences [8], [9].

This article presents a study of adoption of EVs in the Czech Republic administrative areas, as explained by socioeconomic characteristic of these regions. Dynamics of EV adoption are estimated using linear regression. Out of total of 37 possible predictors a subset was selected using technique of stepwise regression.

2 Methodology

The data were collected from the Czech Ministry of Transport Open Data [10] monthly snapshots. For the purpose of our analysis only registrations from years 2019 to 2022 were used, since EV registrations in earlier periods were negligible. The vehicle registration dataset provides spatial breakdown to the level of municipalities with extended powers (ORP).

We selected only personal vehicles, defined as M1 category in the relevant regulation [11]. Vehicle registrations in this category were further split into retail segment, defined as vehicle registrations by individuals (for private purposes) and non-retail segment, defined as vehicle registrations by companies. The retail segment also includes personal vehicles operated by individuals under leasing contracts.

Detailed breakdown of EV over brands and models is presented in Table 1.

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Table 1 Model Breakdown of EV Registrations

Brand	Model	Retail	Non-Retail
ŠKODA	ENYAQ 80	58	1 512
ŠKODA	ENYAQ RS	11	629
ŠKODA	ENYAQ 80X	30	332
ŠKODA	ENYAQ 60	6	202
ŠKODA	other models	0	1
TESLA	MODEL 3	232	692
TESLA	MODEL Y	48	206
TESLA	MODEL S	56	157
TESLA	MODEL X	18	115
TESLA	other models	19	33
TOYOTA	YARIS HYBRID	334	591
TOYOTA	PRIUS	198	63
TOYOTA	PRIUS PLUS	36	18
TOYOTA	other models	85	46
NISSAN	LEAF 40KWH	28	171
NISSAN	LEAF	47	28
NISSAN	other models	42	60
RENAULT	CAPTUR E-TECH PLUG-IN HYBRID	17	112
RENAULT	CLIO E-TECH HYBRID	14	101
RENAULT	MEGANE E-TECH PLUG-IN HYBRID	2	54
RENAULT	other models	8	19
BMW	IX XDRIVE40	2	71
BMW	IX3	3	70
BMW	other models	17	108
SEAT	SEAT LEON SP E-HYBRID150	0	190
SEAT	other models	0	34
other brands	other models	147	435
		1 458	6 050

In order to model consumer activity we focused on retail registrations. Electrification of corporate fleets is expected to contribute materially to the overall reduction of transport CO_2 emissions, but it is best understood as a separate problem, impractical to model based on local socioeconomic variables.

For a deeper illustration consider comparison of Retail vs. Non-Retail EV penetration (Figure 1), noting the high penetration of EV registrations in Mladá Boleslav and Vrchlabí regions; these can be explained better as location of facilities of Škoda Auto than as result of local socioeconomic factors.

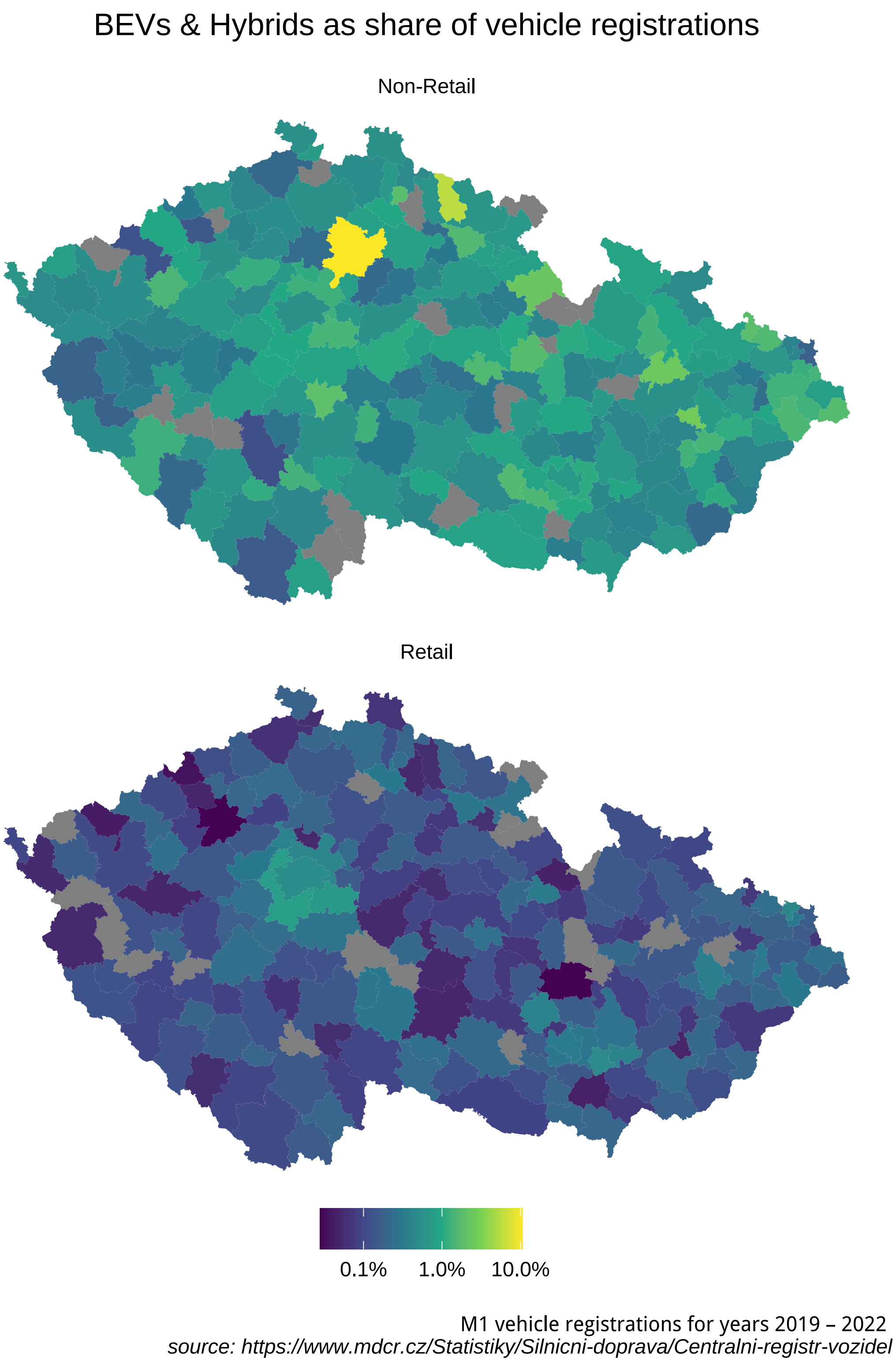

Figure 1 Non-retail vs. Retail EV Penetration (log scale) in Czech ORPs (n = 206)

For the socioeconomic predictors we used results of the previous (2011) census [12]; the results of the 2021 census were not available at the time of writing in the necessary level of detail. The census data were accessed from the Statistical Office API using *czso* package [13]. Data processing and modelling was done in statistical programming language R [14]. Modelling was performed using package *leaps* [15] for stepwise regression. Bayesian information criterion [16] was used as primary metric for variable selection.

Given that the population of the 206 Czech ORPs varies by several orders of magnitude (from more than a million in the capital to less than 10 thousands in Pacov or Králíky regions) it was impractical to model registrations in terms of total registrations per region. Instead relative penetration was used – EV registration as percentage of total personal vehicle registration. Likewise socioeconomic predictors were normalized by population of the ORP.

A basic analysis of spatial dependence – which, if confirmed, would violate two key assumptions of ordinary least squares method, namely homoskedasticity and spatial independence of residuals – was performed using package *RCzechia* [17]. Spatial error was diagnosed via Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity [18]. Spatial autocorrelation of EV penetration at ORP level was measured using Moran's I statistic, as defined in [19].

$$I = \frac{n \times \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \times \sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where $x_i, i = 1, ..., n$ are the n observations, w_{ij} are the spatial weights and S_0 is the sum of spatial weights $\sum_{i,j=1}^{n} w_{ij}$.

The value of the Moran's I statistic of Retail EV penetration was calculated via package *sfdep* [20], using queen contiguity neighborhood definition for determining the adjacency matrix of individual ORPs in order to evaluate spatial dependency of observed data.

3 Result

During the period in question total of 1 451 048 personal vehicles were registered, of which 7 508 could be considered EV's (5 004 battery operated EVs and 2 504 hybrid EVs).

Majority of the EV registrations come from the non-retail segment: 6 050 registrations. Compared to this the retail segment had only 1 458 registrations, which is 19.42% of total EV registrations over the period in consideration.

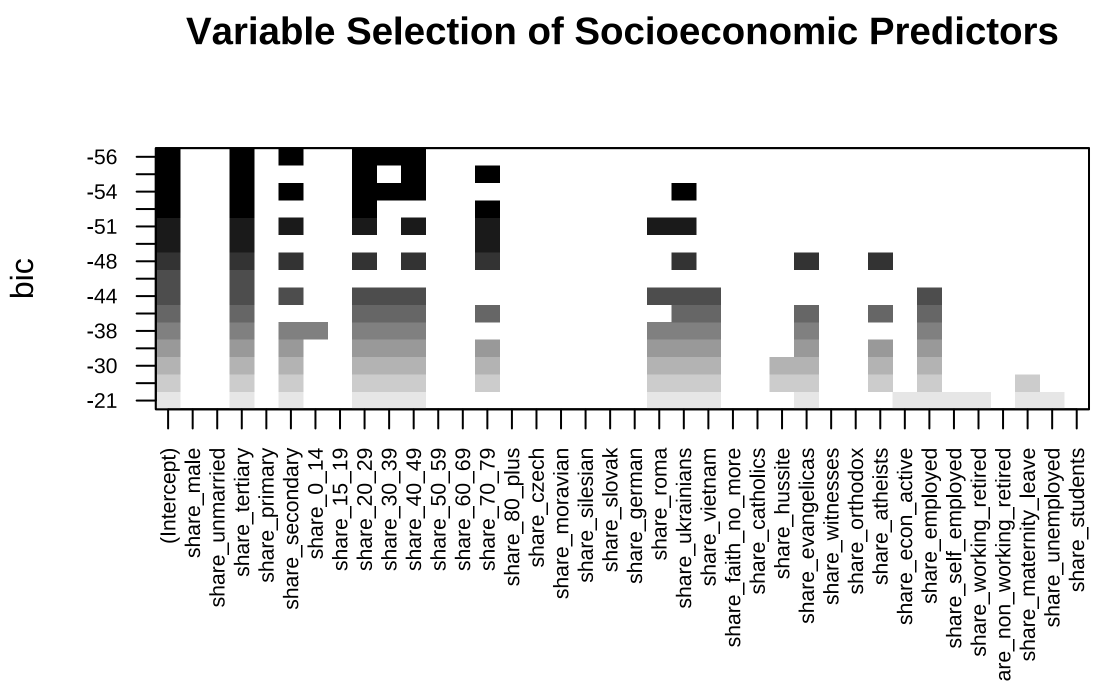

Figure 2 Schwartz's information criterion / stepwise regression

Out of the total 37 socioeconomic variables under consideration we identified the lowest BIC (-56.3035) for model containing intercept and 5 predictors. The predictors and their regression coefficient values are summarized in Table 2:

Table 2 Regression Coefficients

Predictor	Estimate	p-value	Significance [1]
(Intercept)	-0.0026054	0.2802836	
share_tertiary	0.0231548	0.0000000	***
share_secondary	-0.0111012	0.0104673	*
share_20_29	-0.0346544	0.0004860	***
share_30_39	0.0218416	0.0005671	***
share_40_49	0.0428459	0.0007258	***

[1] Using convention: 0 = ***, 0.001 = **, 0.01= *, 0.05 = .

The predictors selected using the stepwise regression approach can be described as:

- *share_tertiary* – ratio of population with tertiary education to population over 15 years of age
- *share_secondary* – ratio of population with secondary education (only) to population over 15 years of age
- *share_20_29* – ratio of population in age bracket 20 to 29 years of age to total population
- *share_30_39* – ratio of population in age bracket 30 to 39 years of age to total population
- *share_40_49* – ratio of population in age bracket 40 to 49 years of age to total population

The coefficients identified via stepwise selection in Table 2 can be interpreted as belonging to two groups: the first related to education - with the share of population with tertiary education leading to higher EV penetration, and share of population with secondary education only leading to lower EV penetration (yet with lower magnitude of the effect).

The second group relates to age structure: share of population in early productive age (20–29 years) drives EV adoption down, and share of population in middle to upper middle productive age (30–39 and 40–49) drives EV adoption up. Other socioeconomic factors, including those related to employment status, nationality and religion, did not have a significant effect on EV adoption as measured by the BIC criterion.

A possible common theme behind the two groups of socioeconomic predictors identified is income. While average income was not one of the census variables considered it is known to correlate with both education level and age [21] – with average wages increasing with education, and peaking in the 40 to 44 age bracket.

The R^2 statistic for our proposed model is 0.3485136, meaning our model does fully explain the variance observed. On the other hand the F statistic is 21.39806, indicating a highly significant relationship.

Based on visual overview shown in Figure 1 we formed a hypothesis of spatial heterogeneity of retail EV penetration – given the noticeable clusters of high penetration in Prague, Brno and their outskirts. To formally validate our hypothesis a test was performed using Lagrange multiplier diagnostics for spatial dependence. The test statistic of 288.419 at 1 degree of freedom strongly indicates a spatial dependence.

In addition the observed value of Moran's I statistic for EV penetration was 0.2615309, with z-score 6.243988 indicating a significant autocorrelation at p-value $2.1327597 \times 10^{-10}$.

Compared to the Moran I test under randomisation for original values, which showed strong autocorrelation, the same test for residuals after linear modelling for the 5 socioeconomic predictors displays much less spatial dependence, with Moran's I statistic of 0.0135323, with z-score 0.4263066. This implies p-value 0.3349422, leading us to reject a hypothesis of spatial autocorrelation of model residuals.

Finally we performed the Lagrange multiplier diagnostics for spatial dependence test on the model fitted for 5 socioeconomic predictors. Test statistic of 0.09510431 at 1 degree of freedom implies p-value 0.7577857, again leading us to reject a hypothesis of spatial dependence.

Thus we confirmed that the socioeconomic model describes the observed data efficiently and that it has removed the observed spatial dependency from EV penetration data, leaving only random effect.

4 Conclusion

We propose a model explaining the dynamics of Electric Vehicles in the Czech Republic retail segment based on socioeconomic predictors at the level of 206 Czech administrative units. The model identified 5 significant predictors (two related to education, and three related to age structure). The identified predictors are variables known to correlate with personal income. While our model did not explain the observed differences in EV adoption over Czech ORPs fully, it did remove the effect of spatial autocorrelation from the data, leaving only random effect.

5 Acknowledgement

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