Explaining spatial differences in PEV acceptance for Trafikdage 2023

Mabit, S.E.*[1], Bunch, D.[2], Jensen, A.F.[3], Rich, J.[3], Thorhauge, M.[3]

[1]Associate Professor, DTU Management, DTU, Denmark

[2]UC Davis, USA, [3]DTU, Denmark

1. BACKGROUND AND PURPOSE

There is an increasing demand for plug-in electric vehicles (PEVs) in many countries. However, the uptake varies across segments within the populations, and across the spatial dimension. Here the spatial dimension related to PEV uptake both covers the geographical differences but also other factors that vary in space such as access to charging infrastructure.

Here we analyse demand variation across regions in Denmark. The research focuses on investigating whether these geographical differences depend on

a) Access to charging
b) Socio-economic effects
c) Attitudinal and perception effects

We divide Denmark into six regions where ownership levels of PEVs are different in revealed preference (RP) data. While the effect of socio-economic variables could be analysed using RP data, there are still some limitations in RP data. In RP data on vehicle transactions, access to charging is rarely known especially for individuals without private charging access. Similarly, attitudes and perceptions are also rarely collected. Finally, while PEV demand have risen in recent years, there is still a limited number of PEV car types available in the market (compared to internal combustion vehicles (ICVs) types). This limits the variability in the attributes describing the vehicles and hence the effects that we try to separate could be confounded if based on RP data due to poor empirical identification.

The paper contributes to the literature through a thorough analysis of the combined effects of geographical regions, access to charging, socio-economic variables and attitudes on vehicle choice especially fuel type choice.

2. METHODOLOGY

The current study is based on a stated choice design (Jensen et al., 2021) that reflects current technology states with respect to three cost attributes, four car characteristic attributes including carbon emissions, and four charging infrastructure attributes. Invitations to participate in the choice experiment were sent out to a representative sample of 25,209 individuals of the Danish population in June 2020 of which 2961 completed the survey. Respondents without a car that are not planning to buy a car have been removed. This reduces the sample from the 2961 respondents in Jensen et al. (2021) to 2745 respondents in this study. Each respondent is asked to answer eight choice tasks.

The paper analyses PEV demand across six regions. These are Copenhagen and Frederiksberg, Greater Copenhagen, Northern and Eastern Zealand, Aarhus, Remaining Eastern Jutland, and Remaining DK.

The analysis applies mixed logit models with random effects that take into account the panel structure of the data as well as unobserved heterogeneity, see e.g. Train (2009). In the most general model formulation, the mixed logit models are included in an integrated choice and latent variable (ICLV) model, see e.g. Ben-Akiva et al. (2002). As neither the mixed logit nor the ICLV models have closed form probabilities, we apply maximum simulated likelihood (MSL) to estimate the models, see e.g. Train (2009).

3. RESULTS AND DISCUSSION

Given the limits on this submission, we keep the descriptive results brief. In Table 1, we have summarised the fuel type shares for the six regions

Table 1: Sample shares across fuel types and regions.

Region	ICV – share	BEV – share	PHEV - share	Total
CPH (1)	973 (0.40)	1041 (0.44)	377 (0.16)	2391
Around CPH (2)	1037 (0.40)	1135 (0.44)	404 (0.16)	2576
GCA (3)	1204 (0.38)	1418 (0.44)	574 (0.18)	3196
Aarhus (4)	518 (0.39)	587 (0.44)	231 (0.17)	1336
Around Aarhus (5)	599 (0.39)	665 (0.43)	272 (0.18)	1536
Rest of Denmark (6)	5077 (0.47)	4114 (0.38)	1723 (0.16)	10914
Total	9408	8960	3581	21949

We use the model in Jensen et al. (2021) without socio-economic interactions as our base model. Therefore, the base model is a mixed logit model with seven random effects. Five for the six car segments (the class of medium cars is used as reference) and two for the three fuel types (the class of ICV cars is used as reference). This model is denoted Model 1. Following this, we estimate 13 model extensions.

An overview of these models is given in Table 2. In models 1-4 and 1c-4c, all model extensions are seen to be significant in Likelihood ratios tests. Concerning models 6-7 and 6c and 7c, we see that there is a minor loss in fit for the choice model in isolation due to the inclusion of a measurement and a structural equation in the estimation.

Table 2: Model overview for models run with 500 MLHS draws. The sample has 21949 observations split on 2745 individuals.

Model	Model description	DoF	Final LL-500
2 v3	Model 1 w. 10 geo dummies added	48	-20932
3 v3	Model 2 w. work charging added	50	-20926
4 v5	Model 3 w. socio-economic interactions added	67	-20866
5 v5	Model 4 tested down	55	-20873
6 v5	Model 5 as ICLV w. attitude 3 added	57*	-20904*
7 v5	Model 6 with SE in structural equation	57*	-20888*
2c	Model 2 with control interactions	58	-20832
3c	Model 3 with control interactions	60	-20819

4c v5	Model 4 with control interactions	77	-20789
5c v5	Model 4c tested down	68	-20793
6c	Model 5c as ICLV w. attitude 3 added	70*	-20831*
7c	Model 6c with SE in structural equation	70*	-20815*

*For the models including latent variables, we only report the LL and the number of parameters (DoF) related to the choice model.

Table 3 presents the regional dummies in Models 2 (the first model with regional dummies) and 2c-7c (the final model).

Table 3: Regional dummies across Model 2 and Models 2c to 7c

Region	Model 2	Model 2c	Model 3c	Model 4c	Model 5c	Model 6c	Model 7c
1 – BEV	1.35*	1.26*	1.28*	0.98*	1.06*	0.41	0.24
2 – BEV	0.84*	0.67*	0.72*	0.58*	0.65*	-0.21	-0.36
3 – BEV	0.94*	0.82*	0.78*	0.71*	0.69*	0.04	0.06
4 – BEV	1.14*	1.05*	1.19*	0.93*	0.96*	-0.02	-0.10
5 – BEV	0.79*	0.68*	0.72*	0.57*	0.55*	0.04	0.07
1 – PHEV	0.61*	0.66*	0.66*	0.50	0.50	0.28	0.16
2 – PHEV	0.48*	0.42	0.46*	0.32	0.34	-0.16	-0.32
3 – PHEV	0.78*	0.77*	0.78*	0.72*	0.71*	0.35	0.38
4 – PHEV	1.01*	1.06*	1.13*	0.89*	0.85*	0.24	0.18
5 – PHEV	0.76*	0.63*	0.65*	0.58*	0.55*	0.48	0.48
Beta_price	-0.71*	-0.73*	-0.73*	-0.73*	-0.73*	-0.71*	-0.71*

The results show the importance of access to home charging related to preferences for PEVs in line with the literature. In addition, the results show that work charging has a significant effect, however this effect is much smaller than home charging, and if combined with home charging the estimates indicate that the combination has approximately the same effect as home charging. The socio-economic variable with the largest effect appear to be education (holding a bachelor level vs. not), however this effect is somewhat confounded with the latent variable (LV) in the final model, and hence becomes smaller and insignificant for BEVs. This LV reflect the perception that BEVs fit well with the daily routine of the respondent. The LV appear to have a positive and significant effect for both BEVs and PHEVs with the largest effect for BEVs. Finally, we note that this does not appear to be driven by non-linear effect of the socio-economic variables in the structural equation in model 7c since the LV parameters are of a similar magnitude in model 6c.

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