Web Appendix: "Sample-based longitudinal discrete choice experiments: preferences for electric vehicles over time"

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1. *Technical appendix*

For the employed method dual response (e.g., Brazell et al. 2006; Schlereth et al. 2018; Wlömert and Eggers 2016), we subsequently detail the covariate-extended hierarchical Bayes logit estimator. For a single choice set a, we calculate the choice and purchase probability $\Pr_{h,i,a}$ of respondent h for alternative i from choice set a as:

$$\Pr_{h,i,a} = \frac{\exp(v_{h,i})}{\sum_{i' \in a} \exp(v_{h,i'})} \cdot \frac{\exp(v_{h,i})}{\left(\exp(v_{h,0}) + \exp(v_{h,i})\right)} \qquad (h \in H,\ i \in I_a,\ a \in A). \qquad \text{(A1)}$$

The first term is the probability of choosing alternative i among the set of alternatives. The second term predicts respondent h's probability of purchasing it, as observed in the second question. This model assumes independence between the two decisions – an unlikely assumption. However, Diener et al. (2006) compared this model to sequential models, such as the nested logit, and found that even the simple model recovers parameter values about equally well.

Given the observed decisions $d_{h,i,a}$ of respondent h for alternative i in each choice set a and the corresponding purchase decisions $d_{h,i'}$ to the previously chosen alternative i', the likelihood function equation (A2) for all choices of respondent h is:

$$L_h = \prod_i \prod_a \left(\frac{\exp\left(v_{h,i}\right)}{\sum_{\tilde{i}} \exp\left(v_{h,\tilde{i}}\right)} \right)^{d_{h,i,a}} \cdot \prod_{i'} \left(\left(\frac{\exp\left(v_{h,i'}\right)}{\exp\left(v_{h,0}\right) + \exp\left(v_{h,i'}\right)} \right)^{d_{h,i'}} \cdot \left(\frac{\exp\left(v_{h,0}\right)}{\exp\left(v_{h,0}\right) + \exp\left(v_{h,i'}\right)} \right)^{1-d_{h,i'}} \right) \ (h \in H). \qquad \text{(A2)}$$

The respondent-specific utility $u_{h,i}$ is:

$$u_{h,i} = v_{h,i} + \varepsilon_{h,i} = X_{h,i} \cdot \beta_h + \varepsilon_{h,i} \ (h \in H;\ i \in I_a). \qquad \text{(A3)}$$

With equation (A4), we allow for heterogeneity of individual parameters through the covariate matrix θ according to a multivariate regression model:

$$\beta_h = \theta \cdot z'_h + \varsigma_h \quad (h \in H). \tag{A4}$$

The matrix θ is a $|P|$ (i.e., number of parameters) by $|Q|$ matrix and contains a set of individual covariates z_h in each row. In the case of just one study, z_h is equal to 1 for all respondents, and θ contains the parameters on the population layer. The error terms $\varepsilon_{h,i}$ and ς_h are assumed to be mutually independent and from multivariate normal distributions with zero means and covariance matrices Ω_h and Σ. Consequently, the vector β_h follows a multivariate normal distribution $N(\theta \cdot z'_h, \Sigma)$. The prior distribution on θ is standard diffuse and has a mean close to 0 and a sufficiently large variance Θ (i.e., $N(\tilde{\beta}\,|0, 5)$). The standard diffuse prior on Ω is inverted Wishart.

The estimator is an extended version of the basic multinomial logit sampler described in Train (2009, p. 302). As a starting point for our implementation, we used the Matlab code provided on Kenneth Train's website. The core of the covariate-adjustment is explained in Lenk et al.'s (1996) Appendix: In particular, the sampling procedure in step 2 and 3, which we transferred to our own implementation.[3] The resulting Markov chain Monte Carlo (MCMC) iteratively generates random deviates from the posterior distribution of one set of parameters given the current value of all other parameters and the data. The required conditional distributions are given in the following steps.

1. Using a Metropolis-Hastings step, we independently generate draws of β_h for all respondents (expressed as $\{\beta_h\}^H$). The conditional posterior of $\{\beta_h\}^H$, given $\theta \cdot z'_h$, and Σ is $\Lambda(\{\beta_h\}^H \mid \bullet) \propto \prod_h L_h(\bullet \mid \beta_h) \cdot g(\beta_h \mid \theta, \Sigma)$, where $L_h(\bullet \mid \beta_h)$ is the respondent-specific

[3] We thank Peter Lenk for providing an implementation of the hierarchical Bayes multinomial logistic regression model in Gauss, which served as a reference for the implementation.

likelihood function from Equation (A2). To account for the fact that some attributes were presented in certain studies, but not in all over time, we set their corresponding parameter values to zero instead of assuming a normal distribution.

2. The Gibbs Sampler for the matrix θ follows the implementation of the covariate extension that is described in step 2 of the model in Appendix A in Lenk et al. (1996). The conditional posterior is $p(\theta \mid \bullet) \propto \prod_{h \in H} N(\beta_h \mid \theta, \Omega) \cdot N(\theta \mid 0, V)$. Also, on the upper layer, we accounted for whether an attribute was included in some, but not in all studies: If the attribute was missing in the reference study, we set all related parameter values to zero. For all other studies, we set them to the negative values in the reference study, such that the sum equals zero.
3. The Gibbs Sampler for the inverted Wishart follows the implementation of Lenk et al. (1996), in particular, step 3 of the model in Appendix A. The conditional posterior is $p(\Omega \mid \bullet) \propto \prod_{h \in H} N(\beta_h \mid \theta, \Omega) \cdot IW(\Omega \mid v^0, s^0)$.

2. *Review of studies on electric vehicles*

Study	Data	Attributes of Interest	Relationship of Price and Range per Charge	Conclusions
Axsen et al. (2013)	21 employees in the U.K.	Purchase price, range per charge, recharge time, acceleration	Price: linear Range: linear	Preferences for electric vehicles can be unstable and therefore changed through learning and exposure. Social interactions can also have an impact.
Glerum et al. (2013)	593 respondents in Switzerland	Purchase price, electricity cost, fuel type, brand, model, incentive, maintenance cost, leasing price, battery lease	Price: non-linear Range: not considered	Large incentives on the purchase price can increase electric vehicle adoption, while too-high operating costs will decrease it. Willingness to pay rises with decreases in the battery's monthly leasing cost.
Ito et al. (2013)	1,531 respondents in Japan	Purchase price, electricity cost, range per charge, recharge time, fuel availability, fuel type, emissions, body type, brand	Price: linear Range: quadratic	Development of an infrastructure for battery exchange stations can be efficient.
Hoen and Koetse (2014)	1,903 Dutch private car owners	Purchase price, range per charge, recharge time, fuel availability, fuel type, monthly cost, number of brands, policy measure	Price: linear Range: linear	Driving range, refueling time, and refueling opportunities lead to lower preferences for electric vehicles compared to fuel cars.
Jensen et al. (2014)	196 respondents in Denmark	Purchase price, electricity cost, range per charge, emissions, charging at home, charging in public spaces, charging at work	Price: non-linear Range: non-linear	Preferences may change, especially if people initially do not have actual experience. The more informed they are, the more positive their attitude toward electric vehicles.
Axsen et al. (2015)	1,754 respondents in Canada	Purchase price, electricity cost, range per charge, recharge time, charging at home	Price: linear Range: linear	Plug-in hybrid electric vehicles are more popular than pure electric vehicles. Interest in plug-in electric vehicles is higher if people have equipment for fast charging at home.
Hackbarth and Madlener (2016)	711 potential buyers in Germany	Purchase price, fuel cost, emissions, fuel availability, refueling time, battery recharging time, policy incentives	Price: linear Range: logarithmic	There is a big preference heterogeneity across potential buyers. Purchase price and electricity cost are relatively unimportant for respondents who prefer electric vehicles.
Our study	In total 1,556 respondents in Germany	Purchase price, electricity cost, driving range, recharge time, motor power, 3-4 complementary mobility services	Price: linear Range: linear	Electric vehicle market is fluctuating with a peak in 2017; preferences stay rather stable.

Table A1: Studies with a focus on electric vehicles

3. Choice set example

1 Please select your most preferred electric vehicle.			
Range per charge	400 km	250 km	325 km
Purchase price	25,000 €	30,000 €	20,000 €
Charging time	1 hour	4 hours	1 hour
Electricity cost per 100 km	5 €	3 €	1 €
Motor power	40 kW (~54 PS)	80 kW (~109 PS)	80 kW (~109 PS)
IT-based parking space and payment	✗	✓	✓
Intelligent charging station	✓	✗	✓
Augmented reality services via head-up displays	✗	✓	✗
	○	○	○

Would you actually buy the chosen electric vehicle?

○ **Yes**

○ **No**

Figure A1: Choice set example

4. *Differences in model performance*

	Covariate-Extended Model	**Separate Estimation**	**Generic Model**
Number of Parameters on Upper Layer	145	475	90
Model Assumption	Explicitly captures the different set of preferences for each sample of respondents, but they are linked through a common covariance matrix	Each set of respondents have an unlinked vector of preference parameters and a separate covariance matrix	Homogeneity in preferences over sets of respondents
Test for significance in changes between samples of respondents	Directly available through the signs of θ draws	Not directly available	Not directly available
Internal Validity Log-marginal density (12 choice sets)	-16410	-16297	-16676
Predictive Validity Log-marginal density (2 Holdouts)	-4765	-5953	-4940
Mean absolute error (between observed and predicted choice shares of 100 respondents, which we left out from the estimation)	6.73%	6.87%	6.77%

Table A2: Differences in model performance

5. *Assessment of the parameter changes in the experimental conditions*

		2019_1_same (reference)	**2019_2_add**		**2019_3_add_remove**		**2019_4_retakers**	
Attributes	**Attribute level**	**Parameter Values**	**Parameter Values**	**Change**	**Parameter Values**	**Change**	**Parameter Values**	**Change**
Constant		-1.52	-1.16		-1.18		-1.27	
Range per charge	Per 100 km	0.60	0.65		0.66		0.69	
Purchase price	per 10,000€	-1.12	-1.21		-1.15		-1.16	
Charging time	1h	0.24	0.28		0.26		0.28	
	4h	-0.24	-0.28		-0.26		-0.28	
Electricity cost per 100 km	1 €	0.96	0.95		1.04		0.89	
	3 €	0.54	0.41	---	0.41	---	0.46	
	5 €	-0.44	-0.33		-0.41		-0.36	
	7 €	-1.07	-1.03		-1.03		-0.99	
Motor power	40 kW	-0.42	-0.27	++	-0.37		-0.40	
	80 kW	0.42	0.27	--	0.37		0.40	
IT-based parking space and payment	Supported	0.42	0.28	---	0.41		0.45	
	Not supported	-0.42	-0.28	+++	-0.41		-0.45	
Intelligent charging station	Supported	0.52	0.35	---	0.45		0.64	
	Not supported	-0.52	-0.35	+++	-0.45		-0.64	
Augmented reality services via head-up displays	Supported	0.22	0.17	-		---	0.13	---
	Not supported	-0.22	-0.17	+		+++	-0.13	+++
Remote diagnostics and update supply	Supported		0.18	+++	0.30	+++		
	Not supported		-0.18	---	-0.30	---		

Note: posterior assessment of change in parameters in comparison to 2019 study: +: >90%; ++: >95%; +++:>99%; -:<10%; --: <5%; ---: <1% positive Δ draws

Table A3: Assessment of the parameter changes in the experimental conditions

6. *Robustness tests*

We tested the robustness of our results in manifold ways. We tested whether the differences in income between the respondents in 2017 and the new ones in 2019 might explain the downturn in the general purchase intention. As income was measured on an eight-point Likert scale, where the last point read "no comment", we employed a propensity score weighting approach that weighted each point according to the inverse probability of belonging either to the 2017 or 2019 sample (known as inverse probability of treatment weighting). The weighted general purchase intentions were 56.17% for 2017 (unweighted: 58.95%) and 44.57% for 2019 (unweighted: between 39.40% and 42.16%). We conclude that the decline in the general purchase intention is robust when controlling for the differences in income. The similarly strong decline of the 2019 retakers compared to their response in 2017 further supports this result.

Another robustness test was the inclusion of income as an additional covariate. We standardized income and used the average in cases where the response was "no comment". The log-marginal density improved further by 25 from -16410 to -16385. This improvement was substantially less than when including covariates for the sample-based longitudinal studies (improvement by 266). Given that importance weights and purchase probabilities were qualitatively about the same, we decided to use the parsimonious model that focuses on sample-based longitudinal studies.

We also tested the linearity assumption for range per charge and purchase price. We used a partworth model for both attributes and treated the changes in their values as new attributes. On the population level, the parameter estimates were ordinal and in the expected direction for both attributes: a higher purchase price always decreased the deterministic utility, whereas a higher range per charge increased it. On the individual level, the standard deviation of the individual mean posterior across respondents were substantially smaller than with a linear model. Adding the partworth model required the estimation of four additional parameters for each respondent, which is a lot, given that only 12 choice sets are available. We thus opted to use the parsimonious model here as well.

Finally, we address case #2 in Table 2 (in our article), i.e., whether explicitly allowing the scale parameter to differ between samples improves predictions. The scale serves as a multiplier of the deterministic utility and is inversely related to error variance, which offers a measure of respondents' decision-making consistency across different data sources. For example, Ellickson et al. (2019) found that accounting for different scales substantially improves predictions when combining *stated* with *revealed* preferences. We implemented a scale-extended hierarchical Bayes sampler together with our covariate-extension (c.f., Schlereth and Skiera 2017) and let one version the scale differ across years (i.e., three scale parameters for 2013, 2017, and 2019); in another version, we let the scale differ across samples (i.e., with six scale parameters). Because the preferences and scale parameters are not simultaneously identifiable (Fiebig et al. 2010; Swait and Andrews 2003), we normalized the scale of the reference study to 1. Neither of the two versions improved log-marginal density, and all scale values were close to 1 (e.g., 1 for 2017, 0.93 for 2013, and 0.90 for 2019). One major difference between Ellickson et al. (2019) and our study is that they joined two completely different types of data sources (namely, revealed and stated preferences), whereas we looked at multiple sets of stated preference data, such that differences in scale are very likely not that pronounced.

References

Axsen, J., Bailey, J., & Castro, M. A. (2015). Preference and Lifestyle Heterogeneity among Potential Plug-In Electric Vehicle Buyers. *Energy Economics, 50*, 190–201.

Axsen, J., Orlebar, C., & Skippon, S. (2013). Social Influence and Consumer Preference Formation for Pro-Environmental Technology: The case of a U.K. workplace electric-vehicle study. *Ecological Economics, 95*, 96–107.

Brazell, J. D., Diener, C. G., Karniouchina, E., Moore, W. L., Séverin, V., & Uldry, P.-F. (2006). The No-Choice Option and Dual Response Choice Designs. *Marketing Letters, 17*, 255–268.

Diener, C., Orme, B., & Yardley, D. (2006). Dual Response "None" Approaches: Theory and Practice. *Proceedings of the Sawtooth Software Conference*.

Ellickson, P. B., Lovett, M. J., & Ranjan, B. (2019). Product Launches with New Attributes: A Hybrid Conjoint–Consumer Panel Technique for Estimating Demand. *Journal of Marketing Research, 56*, 709–731.

Fiebig, D. G., Keane, M. P., Louviere, J., & Wasi, N. (2010). The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. *Marketing Science, 29*, 393–421.

Glerum, A., Stankovikj, L., Thémans, M., & Bierlaire, M. (2013). Forecasting the Demand for Electric Vehicles: Accounting for Attitudes and Perceptions. *Transportation Science, 48,* 483–499.

Hackbarth, A., & Madlener, R. (2016). Willingness-to-Pay for Alternative Fuel Vehicle Characteristics: A Stated Choice Study for Germany. *Transportation Research Part A: Policy and Practice, 85*, 89–111.

Hoen, A., & Koetse, M. J. (2014). A Choice Experiment on Alternative Fuel Vehicle Preferences of Private Car Owners in the Netherlands. *Transportation Research Part A: Policy and Practice, 61*, 199–215.

Ito, N., Takeuchi, K., & Managi, S. (2013). Willingness-to-Pay for Infrastructure Investments for Alternative Fuel Vehicles. *Transportation Research Part D: Transport and Environment, 18,* 1–8.

Jensen, A. F., Cherchi, E., & Dios Ortúzar, J. de. (2014). A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation, 41*, 973–993.

Lenk, P. J., DeSarbo, W. S., Green, P. E., & Young, M. R. (1996). Hierarchical Bayes Conjoint Analysis: Recovery of Partworth Heterogeneity from Reduced Experimental Designs. *Marketing Science, 15*, 173–191.

Schlereth, C., & Skiera, B. (2017). Two New Features in Discrete Choice Experiments to Improve Willingness-to-Pay Estimation That Result in SDR and SADR: Separated (Adaptive) Dual Response. *Management Science, 63*, 829–842.

Schlereth, C., Skiera, B., & Schulz, F. (2018). Why do consumers prefer static instead of dynamic pricing plans? An empirical study for a better understanding of the low preferences for time-variant pricing plans. *European Journal of Operational Research, 269,* 1165–1179.

Swait, J., & Andrews, R. L. (2003). Enriching Scanner Panel Models with Choice Experiments. *Marketing Science, 22*, 442–460.

Train, K. (2009). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.

Wlömert, N., & Eggers, F. (2016). Predicting new service adoption with conjoint analysis: external validity of BDM-based incentive-aligned and dual-response choice designs. *Marketing Letters, 27*, 195–210.