INCORPORATING UNCERTAINTY IN SOCIAL ACCEPTANCE AND ADOPTION IN THE DESIGN AND ANALYSIS OF STATED CHOICE EXPERIMENTS: EXAMPLE OF THE ELECTRIC CAR

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ABSTRACT

Purchases of electric cars may be influenced by market shares of electric cars among members of an ego's social network. Applying the results of a stated choice experiment on the relative influence of relatives, friends, co-workers and peer on the probability of buying an electric car, this paper reports the results of a dynamic simulation for a synthetic social network. Market shares are simulated for a series of iterations, in which the market shares of different members of the social network are used as input to simulate choice probabilities for the next iteration. Results demonstrate the value of this approach and the relative impact of various types of social influence.

Keywords: Social influence, electric car, stated choice experiments, simulation

INTRODUCTION

Stated choice models have become a major approach to forecasting the acceptance and market shares of new products. A set of attributes defining possible designs of the product are systematically varied according to the principles underlying the design of experiments and respondents are requested to indicate their preference for or likely acceptance of the resulting set of profiles. The results of estimated preference or choice models then allow the identification of the relative importance of the experimentally varied attributes to consumer preference and/or choice. By aggregating individual choice probabilities, market size and share can be predicted. If one of the varied attributes is the price of the product, the analyses also allow estimating respondents' willingness-to-pay. If socio-demographics are included in the study, these results can also be obtained at the segment level or the effects of these socio-demographics on preference, willingness-to-pay and market share can be estimated.

In general, one may argue that the predictive success of stated preference and choice experiments depends on (i) whether all influential critical factors have been incorporated in the design and have been correctly represented, (ii) whether the assumed and estimable utility function and choice models represent a valid representation of the actual decision making process, (iii) whether respondents are motivated to provide sincere answers to the experimental task, (iv) whether the researchers have been successful in explaining the purpose of the experimental and task, (v) whether respondents fully comprehend the task, can process the information provided and map it into their own mental representation of the decision problem at hand, (vi) whether respondents can complete the task successfully by generating a valid response from this mental representation and the choice mechanisms they use, (vii) whether the size and complexity of the experiment is within the processing capabilities and acceptable burden of respondents, (viii) whether the implicit assumption that choice behaviour in quasi-laboratory settings mimics adequately choice behaviour in reality sufficiently holds, and finally (ix) whether the actual implementation of the new product is congruent with the description in the experiment.

Most of the requirements apply to any stated preference or choice experiment, irrespective of the decision problem. If the problem involves a new product, some specific problems may arise. Any valid measurement of consumer preferences depends on the articulation of such preferences. If an individual travels by bus on a daily basis and thus builds up different experiences over time, jointly with psychological responses, and learns from repeated choices, one may assume that succinct preferences can be articulated. Preferences are well founded in learned experiences and reinforced psychological states. On the other hand, in case of a new product, by definition respondents do not have the opportunity to experience the product and build-up preferences for that product. Consequently, stated responses depend on perhaps the first time mental representation of the product and associated beliefs, which can are then not based on own experiences but rather on other sources and/or general expectations or associations. Ceteris paribus, the validity of such responses is expected to be lower, compared to the case of learned preferences. Even if the utility function and choice mechanisms would be identical, it is relatively likely that the mental representation is imperfect and will change once more accurate information replaces subjective beliefs.

Moreover, the literature on diffusion processes suggests that the demand for some new product is influenced substantially by acceptance of other consumers in general or specific elements of an ego's social network. Logistic curves have often been used to describe that in the early stages only few consumers will buy a particular product, that once a threshold is crossed, a rapid increase in acceptance may happen after which growth slows down until some satiation level is reached. The relative influence of social networks on the demand of new product depends on the nature of the product. Most products will be purchased on the basis of the utility that consumers will derive from their inherent attribute values. Preference for and utilities derived from other products will depend on preferences of wider social groups, either because individuals wish to belong or be associated with that group, reflected in similar purchasing patterns or because they wish to be disassociated from their group, reflected in incongruent purchasing patterns. Fashion immediately comes to mind. In other cases, the impact of social influence and social networks is not clear.

Scenarios about such markets conditions are typically not varied in stated choice and preference experiments. Designs implicitly assume that individuals choose independently; only some studies have developed stated choice and preference experiments for households. One potential reason for lack of predictive accuracy of stated choice and preference models may be that uncertainty in the general acceptance of new choice alternatives and diffusion rates are not taken into account. It is assumed that individuals maximize their product utility, irrespective of the purchasing decisions of different members of their social network and the evolution of the market share of the new product over time among subsets of their social network.

To take into account the influence of social acceptance and social adoption, and the behaviour of different elements of social network, possible scenarios of linked market conditions should be systematically varied in the design of stated preference and choice experiments. Respondents are then asked to indicate whether they would purchase the new product, considering the specification of the attribute profile and the aggregate market share of the product for different elements of their social network, such as family, co-workers, friends and general peers. This approach was developed and administered in Rasouli and Timmermans (2013), using the demand for electric cars as an example. Using a multinomial logit model to predict choices, this approach allows assessing the impact of different acceptance rates among different elements of a social network.

In further elaborating this study, the aim of the present study is to further empirically investigate the impact of social acceptance and adoption in purchase probabilities of electric cars of a particular profile over time. Assuming some fixed time interval, the market shares of the electric cars among different elements of a social network will change for successive intervals and consequently the choice probability of the egos will also change. This process then leads to aggregate dynamics in purchase probabilities and market shares, which can be simulated by repeated application of the estimated choice model over time.

The paper is structured as follows. First, we will summarize previous stated choice studies on the demand for electric cars to position our study in the wider context of previous research. Next, we will summarize the design and estimation results of the model as background to better understand the elaboration reported in this paper. The design and results of the simulation study are reported in detail next. The paper is completed with a summary of the main findings and a discussion of potential line of future development.

PREVIOUS RESEARCH

Rasouli and Timmermans (2013) provided a detailed account of previous researches on the latent demand for electric and hybrid cars that have been appeared in the literature since the late 1970s. Details of the design of the stated preference and choice experiments are described systematically. In addition to some qualitative focus groups (e.g., Christensen et al., 2010; Lidicker et al., 2010; Cocron et al., 2011; Hinkeldein et al., 2012;) and gaming studies (e.g., Kurani et al., 1994, 1996), the majority of previous research has adopted a stated choice modelling approach. Many of this previous research did not assess the latent demand for electric cars specifically, but rather examined consumer demand for alternative-fuel cars in general (e.g., Brownstone et al., 1996, 1999, 2000; Ewing and Sarigöllü, 1998; Horne et al., 2005 and Mabit and Fosgerau (2011). In general, these studies have applied discrete choice model to estimate the demand for the new types of vehicles. The specific model used generally followed progress in discrete choice modelling. The first studies (e.g., Brownstone and his co-workers (1996, 1999, 2000; Bunch et al., 1993, 1995) used the multinomial or nested logit models, whereas more recent studies are based on the mixed logit (e.g., Brownstone and Train, 1999; Mabit and Fosgerau, 2011), or hybrid model (e.g., Glerum et al., 2011, 2012; Jensen et al., 2012).

As for the attributes varied in the experiments, many studies have adopted a pivoted design, using the current car as the pivot. The number and kind of attributes that have been included in previous stated choice models in this context have varied considerably. All studies included some measure of capital costs. In addition, because some studies were explicitly designed to evaluate particular policies stimulating the use of electric cars, subsidy levels related to the alternative fuel vehicles were sometimes included (e.g., Mau et al., 2008; Axsen et al., 2009). Moreover and as expected, several vehicle attributes have been cruising range, top speed/acceleration and refueling time. Sometimes contextual variables were also included. For example, Ewing and Sarigöllü (1998) considered commuting time, expecting that the interest in purchasing non-gasoline cars may depend on commuter distance, and parking costs. Mau et al. (2008) included warranty, while Potoglou and Kanaroglou (2007a, 2007b) took some specific incentives such as special lanes into account.

This brief overview serves to contend that social influence has not been widely considered in this prior research. At best, the issue has been addressed to some extent in the general description of the experiment. For example, Axsen et al. (2009) randomly divided their sample into three treatment groups. Each group received a different scenario, which differed in terms of the penetration ratios of HEV (between 0.17 and 50%). To mimic consumer learning and effects of word-of-mouth, each scenario included hypothetical information from a newspaper, manufacturer brochure and personal testimonials, communicating uncertainty about the technology and the availability of models. Studies, however, which systematically varied market penetration rates, do not seem to exist.

DESIGN AND RESULTS OF STATED CHOICE EXPERIMENT

In an attempt to enhance the state of the art on estimating the latent demand for electric cars Rasouli and Timmermans (2013) expanded the number of potentially relevant attributes in the experiment, and estimated the effects of general reviews and social influence of different elements of social networks, while avoiding some potential methodological limitations, such as the lack of blocking, inclusion of panel effects, and use of pivoted experiments of previous stated choice and preference studies. In particular, they constructed an orthogonal fraction of the $8^2 \times 4^9$ full factorial design in 128 runs. The principle of attribute balance was satisfied, implying that the 8-level attributes appeared 16 times in the overall design, whereas the 4-levels attributes occurred 32 times. The following commonly used attributes were systematically varied in the experiment: the price of the electric car relative to the price of an equivalent standard car, the costs of fuel, the range of the car, the time required to (re-) charge the battery, the maximum speed of the car. In addition, distance to a charging station was experimentally varied. Respondents were instructed that distance should be interpreted in terms of closest distance from their main activity location (home, work, etc.). In addition, however, another set of factors describing possible reviews and adoption of this new technology among various elements of social networks was added. This set of attributes allows assessing the impact of social adoption by family, friends, colleagues and the larger social network of peers and the impact of the nature of reviews (positive or negative) after the introduction of the electric cars. Respondents were asked to indicate whether they would buy an electric car of the given profile of attribute levels as respectively their first car, second car and whether they would rent it, considering the described reviews and behaviour of different members of their social network.

A multinomial logit model was estimated based on the responses of sample of 726 respondents who completed a Web-based questionnaire survey in June 2012. The estimated effects of reviews and social network elements were relatively small, but interesting part-worth utility curves were found. Table 1 gives the estimated results. Except for peers, the part-worth utility first monotonically increases with a larger share of electric cars among members of that subset of the social network. The share that marks a change from increasing to decreasing utility is lower for relatives. In contrast, the curvature of the part-worth utility function for share of electric cars among peers is asymmetrical U-shaped. This may evidence that buying an electric car may differentiate them form their peers in terms of the car they own. Utility then decreases until reference point after which utility monotonically increases with increasing share of electric cars among peers. This may evidence the desire to conform to their peers in terms of the car they own.

Table 1 - Estimated coefficients

Variable		Coefficient	St. Error	p-value
Constant		-1.8779192	0.0778927	0.0000
Price	35% more expensive than gas	-2.8972851	0.2203597	0.0000
	25% more expensive than gas	-1.2090573	0.1922248	0.0000
	15% more expensive than gas	-1.3889438	0.1859013	0.0000
	5% more expensive than gas	-0.0194329	0.1534481	0.8992
	5% less expensive than gas	1.25822561	0.1381815	0.0000
	15% less expensive than gas	1.44240742	0.1330313	0.0000
	25% less expensive than gas	1.64669209	0.1278168	0.0000
	35% less expensive than gas	3.04531322		
Costs	35% more expensive than gas	-2.2357999	0.2157384	0.0000
	25% more expensive than gas	-1.2238625	0.1879169	0.0000
	15% more expensive than gas	-1.7663815	0.1900334	0.0000
	5% more expensive than gas	-0.7671852	0.2130658	0.0003
	5% less expensive than gas	1.36865378	0.1306988	0.0000
	15% less expensive than gas	0.45943645	0.1383271	0.0009
	25% less expensive than gas	2.08353192	0.1176028	0.0000

	35% less expensive than gas	2.08160693		
Range of the car	100 km	-1.8751963	0.1282985	0.0000
	250 km	-0.3741821	0.1076702	0.0005
	400 km	0.96421818	0.1001923	0.0000
	550 km	1.28516019		
Time to charge battery	5 min change battery	0.42854918	0.0919717	0.0000
	1 hours charging battery	0.06159372	0.0943521	0.5139
	4 hours	-0.0146533	0.09873	0.8820
	7 hours	-0.4754896		
Max speed car	80 km-hr	-1.3693717	0.1144456	0.0000
	120 km-hr	0.23023681	0.1023573	0.0245
	160 km-hr	0.39144425	0.0943428	0.0000
	200 km-hr	0.74769065		
Distance to charging station	At home	0.1118134	0.0938515	0.2335
	1 km	0.20182269	0.0957915	0.0351
	5 km	-0.3319772	0.0953075	0.0005
	10 km	0.0183411		
Variable		**Coefficient**	**St. Error**	**p-value**
Share friends	0%	-0.0265385	0.1008464	0.7924
	25%	0.26464983	0.0948506	0.0053
	50%	0.07258828	0.0948012	0.4439
	75%	-0.3106996		
Share family	0%	0.00607518	0.1015649	0.9523
	25%	0.04713752	0.0988568	0.6335
	50%	-0.0187189	0.0981864	0.8488
	75%	-0.0344938		
Share colleagues	0%	0.09130612	0.0966261	0.3447
	25%	0.3691472	0.0958622	0.0001
	50%	-0.0423296	0.1027857	0.6805
	75%	-0.4181237		
Share peers	0%	0.1345657	0.093804	0.1514
	25%	-0.3076537	0.1009052	0.0023
	50%	-0.0222957	0.0953677	0.8152
	75%	0.19538366		

SIMULATION

In order to examine the effects of including social influence on the evolution of market shares, a numerical simulation was conducted. This simulation involved the following steps:

1. Create a synthetic social network

2. Formulate a scenario regarding the attributes levels of the electric car varied in the stated choice experiment
3. Given these attribute levels, calculate the utility of an electric car for each member of the social network of each simulated individual, considering the shares of electric cars for each of these types of members of the social network
4. Using the resulting utilities, use the estimated multinomial logit model to calculate the probability of buying an electric car for each member of the social network of the individuals
5. Use Monte Carlo simulation to decide whether a member of the social network will buy an electric car for each member and individual of the synthetic social network
6. Repeat steps 2 to 5 for a fixed number of iterations.

Note that in the first iteration only vehicle characteristics were taken into account, which results in the same probability of buying electrical car for all individuals. Monte Carlo was applied to draw realisations.

Creating a synthetic network

To perform the simulation, it is critical to create 4 types of members of the social network. In the present study, the created network consists of 10000 individuals. First, for each individual, the number of family members was simulated based on the empirical distribution extracted from dedicated social network data (van den Berg et al., 2009). Next, for each individual, the same data set was used to simulate for each individual the number of friends, co-workers and peers. Social ties within the simulated network of 10000 individuals were simulated by randomly selecting individuals, imposing the constraints of reciprocity, non-overlap between the four kinds of members and simulated social network size by kind of member. Reciprocity means that if individual *j* belongs to the social network of individual *i*, *i* belongs to the social network of *j*. Non-overlap is required because the four categories (relatives, friends, co-workers and peers) are considered mutually exclusive. The third constraint is required to avoid the possibility that the number of sampled members of an ego's social network in any category may be inconsistent from the initially sampled network size for that category. Table 2 gives the average number and standard deviation of the synthetic social network size for each of the four categories. It shows that synthesized values are close to sample values (van den Berg et al., 2009).

Table 2 - Statistics of social network size

Synthesized network				
	Family	Friends	Colleagues	Peers
Average	10.93	8.82	1.7784	1.3854
Std	6.17	6.03	1.98	2.97
Van den Berg et al.				
	Family	Friends	Colleagues	Peers
Average	10.09	8.22	1.71	1.47
Std	6.971	6.719	2.667	3.322

Formulating scenario

The following attribute levels were selected to initialize the study and formulate the scenarios.

1. The price and cost of electrical car is 5 per cent higher than the gasoline engine.
2. Range of car is 250 km
3. Time to charge battery is 1 hour
4. Maximum speed of the car is 120 km/hr.
5. Distance to charging station is 1 km

These attribute values were chosen because they represent current electric cars functionality best.

Calculating utility and choice probabilities

The utility of an electric car was calculated by multiplying the matrix of individuals by coded attributes levels of the electric car of the scenario profile by the estimated coefficients of the estimated choice model. Because in this first study we did not include the effects of selected socio-demographic variables, the corresponding coefficients for the socio-demographic variables were set equal to zero, implying that average socio-demographic effects were simulated. The resulting utility was then used to calculate the probability of buying an electric car using the multinomial logit model.

Monte Carlo simulation of individual realisations

The previous step results in predicted choice probabilities. Monte Carlo simulation was used to identify whether a specific individual will buy an electric car or not. This means that the calculated choice probabilities for each member of an individual's network, considering the type of member (relative, friend, co-worker and peer), were translated into the proportion of a fixed range. Next, a number was drawn from this range at random. If this randomly selected number falls in the interval representing the decision that an electric car is bought, the member is simulated to have bought an electric car. If the random drawn number falls outside this interval, the member is simulated not to buy an electric car.

Iterations

For each individual, these simulated decisions were aggregated into market shares by type of member and these market shares were then input for the next iteration. Because the multinomial logit choice model was estimated for discrete categories of market shares, the estimated utilities for the simulated shares were linearly interpolated from the estimated part-worth utility functions. These interpolated values were then used in calculating choice probabilities in the next iteration.

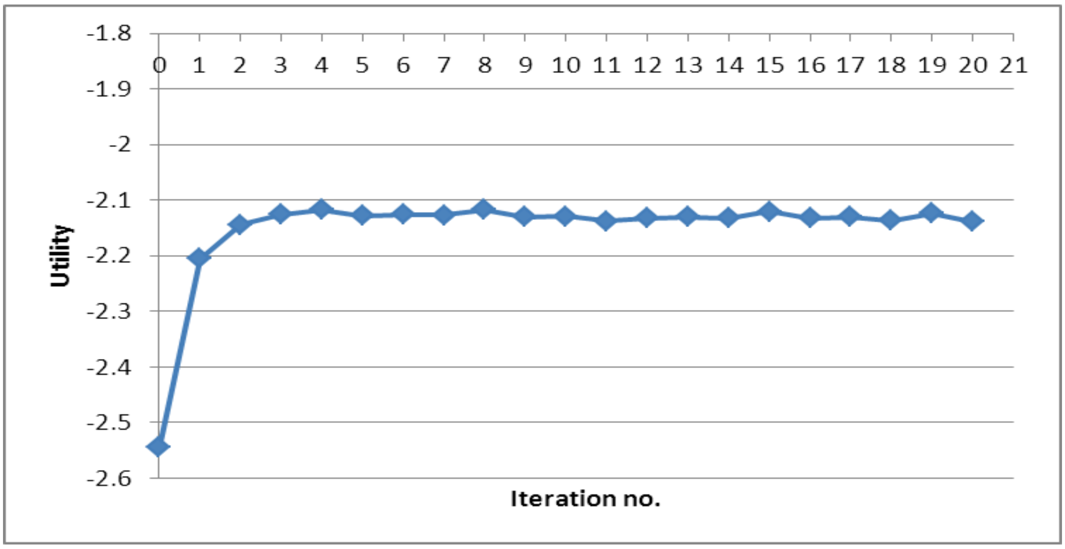

Figure 1 - Average utility of buying an electric car (all social influences)

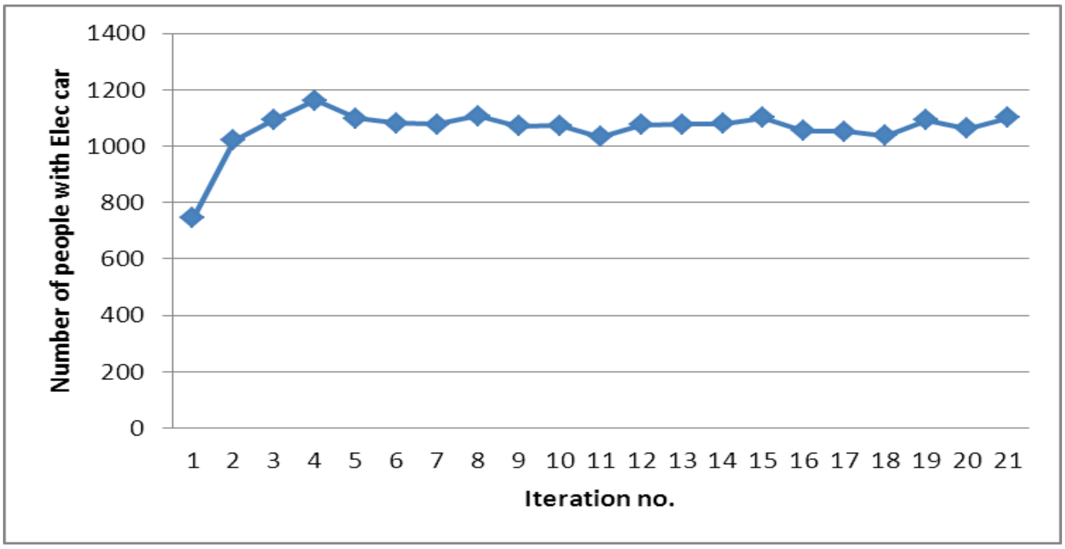

Figure 2 - Number of people who buy an electric car (all social influences)

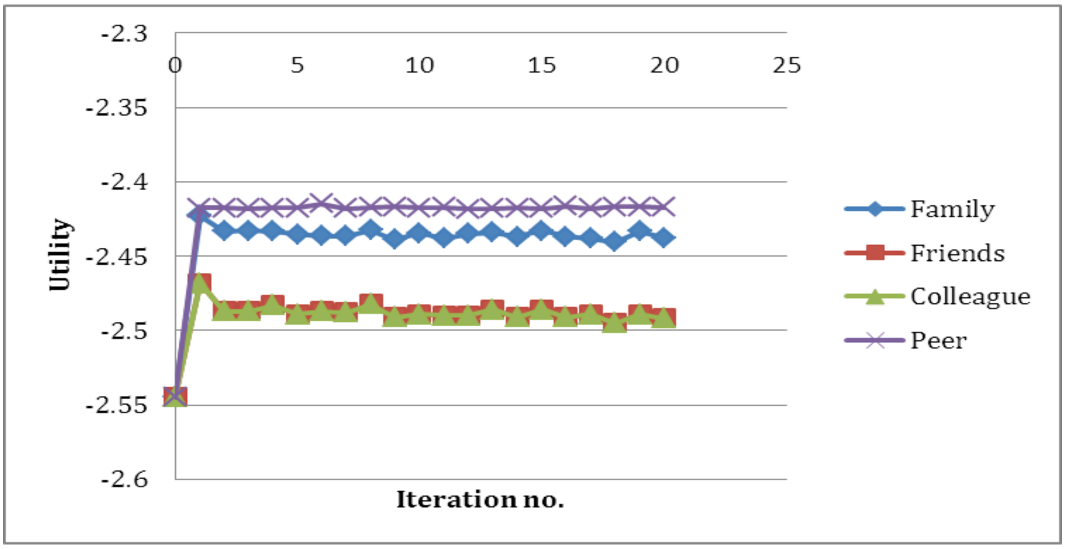

Figure 3 - Average utility of buying an electric car by kind of member

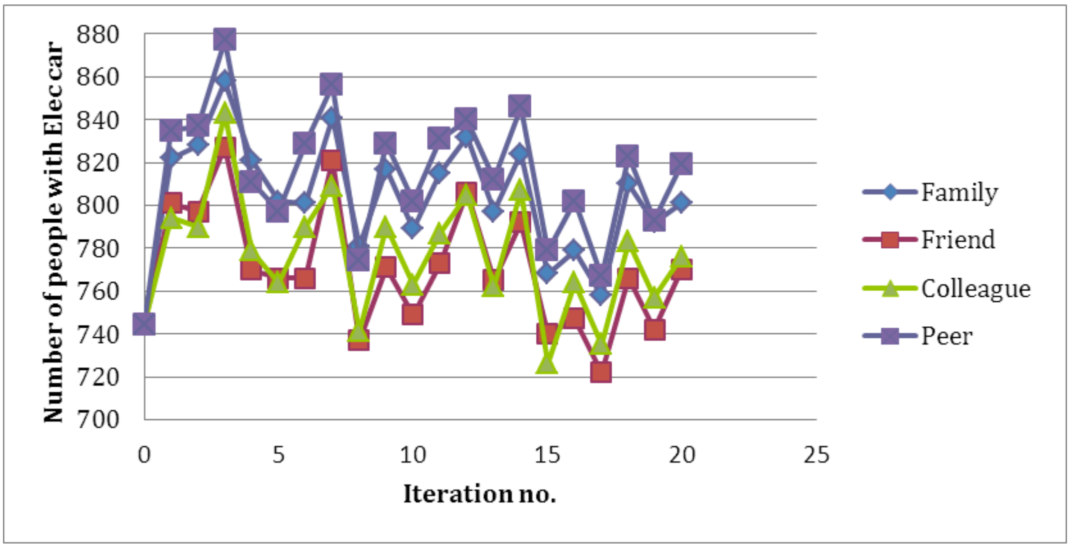

Figure 4 - Number of people who buy an electric car by kind of member

RESULTS

Figure 1 illustrates the average utility of buying electric car in successive iterations. The minimum utility is obtained when no social network impact is considered (-2.54) and maximum utility is related to iteration 9 (-2.1171). The figure shows that utility tends to become stable after a few runs. Figure 2 portrays the results of the simulation. It shows that without social influence effects, 744 individuals out of 10000 are simulated to buy an electric car. They represent a market share of 7,4 per cent. Note that a standard application of a stated choice experiment would have this market share as its outcome. The inclusion of social network effects increases market share to around 11 per cent in a few iterations after which it stabilizes.

Because these figures represent the overall effect of the influence of different components of a social network (relatives, friends, co-workers and peers in general) and the influence of these different components differ in size and across time, the effects of each of these components of a social network on time-varying utility and the evolution of the market share of electric cars were also simulated separately, assuming the effects of other components of the social network are equal to zero. Figure 3 shows that the amount of impact is higher for peers, followed by relatives (family) and colleagues and friends. It also shows that the effects of peers, compared to the other member types are more constant in the dynamic simulation. The dynamic evolution by kind of member shows a fluctuating but downward trend of decreasing market share.

CONCLUSIONS AND DISCUSSION

Applications of stated choice experiments commonly do not take social influence into account. Ignoring social influence may affect the accuracy of the forecasts of stated choice models when individual choice behavior is influenced by accumulated choices of other individuals at any particular moment in time. Purchasing decisions of electric cars may be an example reflecting behavior with relatively significant social influence.

In a previous publication, we suggested a straightforward approach to include potential effects of social network in the design of stated choice experiments. In particular, the market shares of the electric car were systematically varied for relatives, friends, co-workers and peers and respondents were asked to take these market shares into account, in addition to the usual attribute values, when deciding whether of not to purchase an electric car.

The aim of this paper was to apply the estimated choice model to a synthetic social network and examines the effects of introducing the social influence effects on estimated market shares of the electric car in a dynamic context. To that effect, the predicted market shares for four kinds of social network members were used as input to the choice model in the next iteration.

Two important conclusions may be drawn. First, results of this simulation study suggest a difference between market share predictions between including and not including social influence. Secondly, the dynamics indicate that market shares arrive at a stage of quasi-equilibrium after a few iterations. The approach reported in this paper is a first of a larger, more elaborate dynamic simulation approach. We intend to elaborate the approach in various ways to avoid the current limitation of a comparative static approach. First, the effects of socio-demographic variables can be added to the current approach. It implies that their effects on choice probabilities should be estimated from the stated choice data. In addition, the creation of the synthetic social networks needs to be expanded and link socio-demographic profiles to social links, while satisfying the marginal distributions of the various socio-demographic variables. This is a challenge in its own right; we are not aware of a previous approach to synthesize both size and socio-demographics profiles of social networks. Second, in addition to observed heterogeneity, unobserved heterogeneity might be included in the simulation. This would acquire a substitution of the multinomial logit model by the mixed logit model. It would also imply that in calculating utilities Monte Carlo drawn from the mixing distributions are required. Finally, in the current simulation, the population of individuals potentially interested in buying an electric car is static. This is not very realistic in the sense that state-dependency is likely to occur. In order to incorporate this aspect, a model of vehicle holdings, allowing one to simulate whether an individual is considering purchasing a car as a function of the time elapsed since buying the current car, should expand the current model. We plan to report on such elaborations in future publications.

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