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Informing agent based models with discrete choice analysis: diffusion of solar PV in the Netherlands

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I. Introduction

Discrete choice models (DCM) are well known in econometric literature and widely applied since the 1970s. These models are used to predict market shares of products or to estimate demand for services and transport or to assess people's compliance to certain policies. DCM provide statistical estimates of people's preferences and behaviour. However, DCM come with limitations that they provide *static* account of preferences. In reality, preferences change as consumers interact with one another or in response to market fluctuations [1], [2]. Simulation models, on the other hand provide *dynamic* representation of affairs. More specifically, agent based models (ABM) simulate interactions and dynamic behaviour of people, and capture emergent patterns [3]. Putting the two approaches together, one can first use DCM to obtain information on current tastes and preferences of individuals, and then use the analysis provided by DCM to create ABM,thereby, introducing dynamics in preferences to assess the outcomes of potential measures or scenarios on people's behaviour [1], [4], [5].

Dia [6] and Vag [1] proposed that ABM can provide better understanding of consumer behaviour, if people's preferences and attitudes are supplied by conventional surveys. Moreover, the interaction of demographic variables (e.g. age, income and education) with people's choices [7] and also influence of social networks [8] can provide even more insights to behavioural aspect. However, these studies do not provide a structured path to describe how data from empirical experiments, such as discrete choice, can be incorporated into ABM.

This paper aims to provide a methodological framework in which combining these two modelling approaches can be realized. Furthermore, we apply these concepts, on the case of large scale adoption of solar photovoltaic (PV) panels by Dutch home-owners.

II. Methodological Framework

In this study, we introduce a methodological framework, which provides a path on how to incorporate outcomes of discrete choice experiments in agent based models. Figure 1 displays this framework.

In the first part our framework (left side of figure 1), a discrete choice experiment is shown. As an input to this type of experiments, domain related information, attributes and influential characteristics of the product or service under study are gathered by the researcher(s). At this stage, norms (i.e. social norms, which according to Ostrom (2009) are informal rules in society that are accepted and complied with by individuals [9]) can already be included in discrete choice experiments [10]. Besides these, interaction of demographic and attitudinal variables with respondents' preferences can be captured through DCM [11].

When a discrete choice experiment is performed, respondents are asked to select among alternatives offered by a survey, and thereby reveal their preferences based on attributes that are featured in alternatives. DCM estimate coefficients for product attributes, which displays the weight attached to them by respondents. These coefficient are then included in the decision making process of agents in ABM.

In the second part of our framework (right side of figure 1), the agent based model is conceptualised. Agents are assigned with properties [12] based on demographics obtained from respondents. Agents are also populated with the attitudes of respondents. These attitudes concern respondents' general approaches and beliefs, in wider perspective, concerning the implication of consuming a product or using a service under study. These are assigned to agents as personal values [12]. These properties and personal values, together, define agent's state [13].

Staying with the ABM part of the framework, we refer to the environment box. The environment, in which agents interact, provides some physical and social components that resemble the real world. For instance the agents have only limited access to solar PV market and the PV systems can only supply a certain amount of power to each house. The social components refer to the influence of society on individual's behaviour; for instance the level of uptake of solar PV technology in a neighbourhood/social network may influence the owners of a house to install panels. These components are investigated at initial stages of the choice experiment and presented in similar form in ABM to provide consistency between the two modelling approaches.

Finally, the agent behaviour box is the heart of decision making and processing part of the ABM. This box includes the decision making process of agents and the weights they assign to attributes, which together enable an agent to choose the most suitable alternative based on its characteristics. The choice behaviour of respondents and the variance of their preferences are taken from the DCM and applied in this module of the ABM. As well as preferences, the agents' state (i.e. properties and personal values) and environmental aspects are included

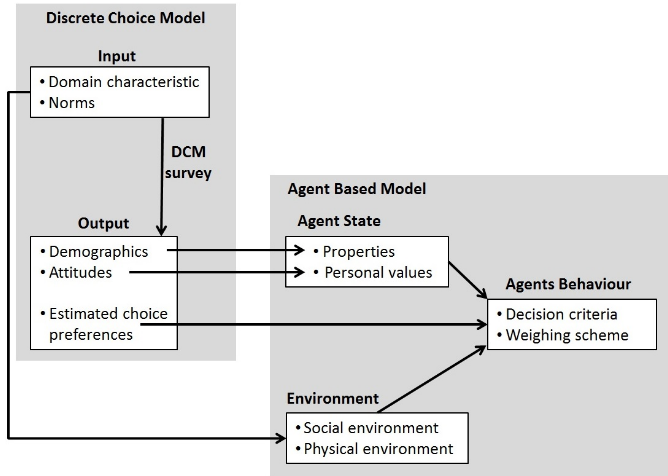

Figure 1. A methodological framework to combine discrete choice experiments with agent based models

in the decision making process. Putting all this information together, agents are equipped to choose the alternatives, which are similar to the products at the market.

Agents obtain a certain amount of utility from each product (i.e. solar PV systems) based on the values of product attributes. If the utility obtained from an alternative meets the threshold utility of an agent, then that agent will buy the product or adopt the innovation or use the service. If the threshold limit is not met by any alternative, then agents leave the process of decision making and wait for the next round of decision making (i.e. next tick). In the next round some changes may occur at the market (e.g. new prices or new product attributes) and also to agent himself (e.g. age, income, or disposable allowance to spend on the alternatives or changes in social network).

III. The case of Solar PVs in the Netherlands

We use the case of large scale diffusion of solar PVs in the Dutch houses as a platform to describe the functionality of our framework. Solar photovoltaic panels are popular technologies for domestic use, with an installed capacity of 51 GW in Europe as of 2011 [14]. The market for these panels is still expanding, despite the financial crisis between years 2008 and 2012. The Netherlands is currently ranked 13th in installed capacity, while its neighbouring countries, Germany and Belgium, are 1st and 6th respectively. The installed capacity of solar PV in the Netherlands is expected to grow, calling for more analysis on consumer behaviours and attitudes with respect to sustainable energy supply. Previous studies have described some common characteristics in the demographic variables of the majority of ”early adopters” of PV systems in Groningen [15]. Other studies have developed ABMs of adoption of solar PVs [16]. At each time-step, agents assess the relative attractiveness of the comparable technologies which then allows them to decide whether to continue using current technology (obtaining electricity from the grid) or to adopt a new power supply (decentralized generation).

Veneman [17] reviewed number of ABM on distributed generation technologies, emphasizing that models developed to study diffusion of decentralized technologies are mostly ”theoretical”, and there is a need to ”combine empirical methods with agent-based modelling” . This is where our proposed framework becomes relevant.

IV. Framework implementation on the PV case and model narrative

The survey on Dutch households is not yet completed, therefore we used a data set from another choice experiment, with a comparable product, as our synthetic data set. The main aim in this paper is to develop an ABM based on discrete choice data and use DCM analysis as the basis of decision making process of the agents.

In the DCM part of the framework, the preferences of respondents is estimated for four attributes of solar panels: initial investment (in euro/Wp), recyclable parts used in PV (after its life time)[in %] , free maintenance support (in monthes) and efficiency of the PV system (in index system). With the data gathered and processed in the DCM part, we calculate the utility derived from PV alternatives by each respondent and record these in a data file for ABM.

Additionally, instead of using a single set of (averaged) coefficients for everybody, we used latent class analysis to categorize our respondents into 3 latent segments that have congruent choice behaviour or preferences within each segment. Latent class models are applied in DCM to estimate segment specific coefficients [18]. These coefficients are then included in agents' decision making processes in our ABM. This allows for consideration of heterogeneity in preferences and choice behaviour among home-owners.

Next, we shift to the ABM part of framework. For this part, an agent based model has been developed using Netlogo platform. For each respondent in the survey there is an agent in the model with its demographic characteristics and coefficients (preferences) - according to the latent class the respondent belongs to.The model is initialized by creating a social network

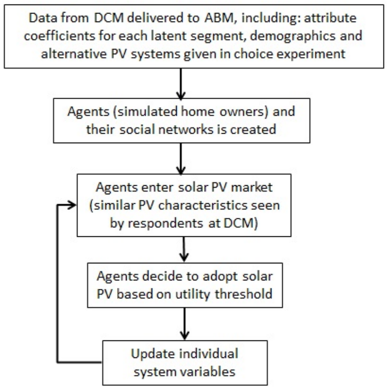

Figure 2. Flow map of ABM for solar PV diffusion in Dutch households

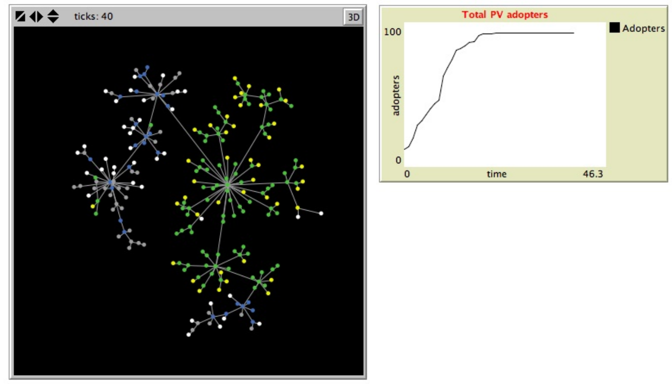

Figure 3. Screenshot of ABM for diffusion of PV systems in Dutch houses

of 238 agents representing this number of respondents from the survey.

Figure 2 shows a conceptual flow map of the ABM model for solar PV diffusion. During the model run, agents decide to enter the solar PV market or not. The decision to enter the market happens when agents have the “intention” to adopt a PV system. Agents’ intention are directly influenced by percentage of PV owners in their social network, who own PV system. When a certain percentage of agents (determined by the modeller at set-up stage) have adopted a PV systems then the individual agent in a given social network has the intention to enter the market. In the next step, the agent assesses some random number of PV systems in the market and calculates the utility it derives from each alternative PV system. These alternatives have similar attributes as the ones offered at the discrete choice survey, so that agents face the same situation as respondents in the market.

The decision to adopt one of the solar PV systems is based on the utility maximization mechanism. The alternatives can have a different utility value for different agents, since it depends on their coefficients. Agents have segments specific set of coefficients by which they give weight to the four attributes of the PV system. These coefficient sets are taken from latent class analysis in DCM data, which was explained earlier. Thus, when agents from different segments consider the alternatives, they derive different utilities. Next step in the agent based model, agents compare the utility of their selected PV with their “threshold Utility”. If the utility of chosen PV system passes the threshold then agents adopt the candidate PV, otherwise the agents do not adopt and leave the market. The “threshold” is calculated as the highest estimated utility from the DCM data set.

V. Results

A screen shot of the ABM is displayed in figure 3. In this particular netlogo model run, there were 5% initial adopters, 15% PV owners in network required for “intention”, and no change in the original threshold utility. Home-owner agents are represented by dots and are connected in a social network via the grey lines. Initially, agents in different latent classes have different colors (grey, blue, white). Agents turn yellow when they enter the market, and eventually turn green if they adopt. The graph on the right side of figure 3 shows the PV adoption curve.

After running the model over 2420 runs and processing the ABM outputs with R [19], we arrived to results displayed in three consecutive figures 4,5,6, showing the total number of agents adopting solar PV systems in different circumstances. Figure 4 shows the impact of initial PV owners on eventual diffusion of PV systems. As the initial adopters increase from 1% to 15% of agents, one can see that final number of adopters also increases. This indicates the rate of diffusion of solar PV has a strong dependence on the current population of PV owners.

As mentioned earlier, agents decide to enter the PV market only when they have intention. This intention is linked to the minimum number of adopters, in each agent’s social network. In figure 5, when the minimum number of PV owners (required to trigger agents’ intention) increase, the final aggregate number of adopters decline. This implies that, if agents require many peers to adopt before deciding to enter the market, then the diffusion rate would be low.

Finally, the utility threshold of agents are varied (accordingly) to higher or lower levels of original thresholds in figure 6. When the threshold is lowered, agents became less stringent in their selection procedures and adoption rates increase. Conversely, when the threshold levels are increased, indicating captious agents, the adoption rates stay low and almost constant to some specific number of agents.

VI. Conclusion

The proposed framework provides an empirical foundation for developing ABM. Furthermore, the behaviour of agents and those of ”real life” respondents can be compared using base case scenarios, where alternatives and environmental factors of the survey and the ABM are similar. In this way, the initial outputs of the ABM can be validated. ABM simulate dynamic choice situations and different scenarios can be exercised. This can be insightful to study emerging patterns from changing market and environmental situations.

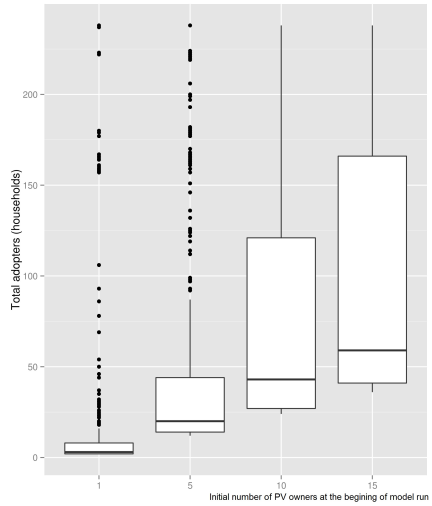

Figure 4. Diffusion of solar PV when the initial PV owners are increased

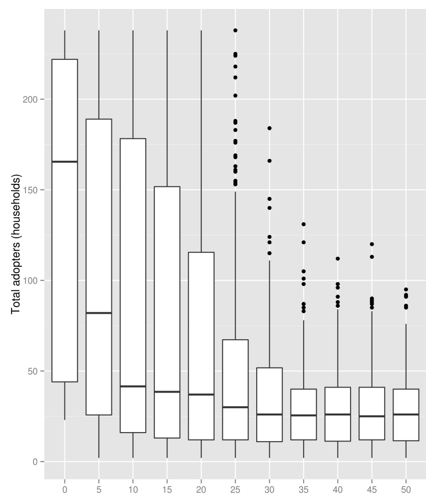

Figure 5. Diffusion of solar PV when minimum required percentage of PV owners in agents' social network is varied

This is a benefit of ABM that can not be easily achieved by conventional discrete choice experiments.

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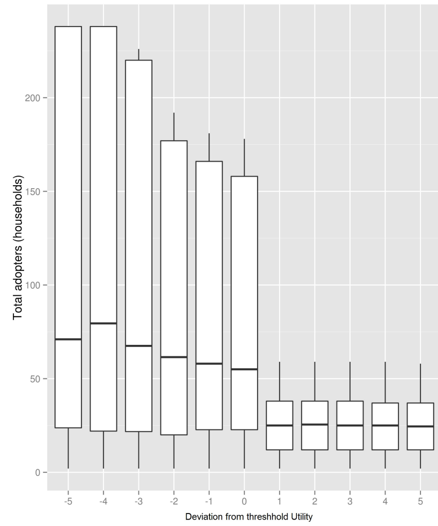

Figure 6. Diffusion of solar PV when agents' utility threshold is varied

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