Extended Abstract

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Paper/Poster Title	Spatially allocating preferences derived from a choice experiment: a comparison of two methods

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Abstract	***200 words max***

In the last decades, stated preferences analyses proved to be useful to guide policy making, in particular when it results in the expression of individual preferences for different policy options. However, when it comes to spatial planning policies, the usefulness of results such as averaged individual or group preferences may be limited for decision-makers, since spatial heterogeneity of preferences is strong in most cases. In this situation, when the greatest adherence to a planning policy is sought, the adaptation of policy options to the socio-demographic characteristics of inhabitants and spatial context may be required. In this paper, we try to determine the best method and practices to spatially allocate and map the preferences obtained from discrete choice experiments. To do so, we compare two methods of estimation and spatial allocation of preferences and evaluate their performances at representing the spatial heterogeneity of preferences at a small geographical level. First, we employ Monte Carlo simulations with the two approaches, making different assumptions on the data generating process, to determine which method performs better in theory. Then, we apply the methods' comparison to the case of light pollution mitigation policies in Montpellier Metropolitan Area (MMA, France).

Keywords	Discrete choice experiment, spatial heterogeneity, spatial planning, light pollution, social preferences, mapping.
JEL Code	Q57, R58, D69 see: www.aeaweb.org/jel/guide/jel.php?class=Q)

Introduction	***100 – 250 words***

Discrete choice experiments are proved to be useful to guide policy making, in particular for the elicitation of individual preferences for different policy options. However, results are usually presented as average preferences among a population, which may be of limited usefulness for spatial planning policies in which spatial heterogeneity of preferences is strong. In order to spatially allocate preferences derived from a DCE, an ideal solution would be to model the choices directly at the locations of interest. However, collecting data is costly and the number of respondents per location is often quite low and not representative of the population in that geographic area. Therefore, one needs to find a solution to extrapolate the willingness-to-pay (WTP) for different goods in the locations of interests.

In this paper, we propose two methods that use the influence of socio-economic and spatial variables on the general preferences of the population to predict average WTPs at small geographical scales. The first method, that we call the "one-step" method, consists in including the control variables directly into the model, through interactions with the attributes. The second method, the "two-step" method, first involves estimating a Random parameter logit (RPL) model without control variable. Individual WTPs are then estimated from the model results. In the second step, these individual WTPs are regressed on the control variables. To predict the average WTPs, we apply the functions derived from both methods to the socio-economic and spatial characteristics of each geographic area (that can be obtained in the general census).

Methodology	***100 – 250 words***

We conduct Monte Carlo simulations to compare the two methods. In these simulations, a population of 500,000 individuals is divided into 9 geographical zones. For each replication, we draw a sample of 1000 individuals, who choose their preferred alternative for 10 choice cards, whose attributes are also simulated. The choice of the respondents depends on their preferences, which are simulated. Since we assume that preferences depend on socio-economic and spatial variables, we include a variable in the definition of the parameter of the preferences. Therefore, individuals' preferences depend on their revenue, a variable that varies both within and between zones. Simulations are replicated 100 times. For each replication, we estimate the model parameters using both methods. In order to assess the robustness of the performance of the two methods to the setting of the simulations, we propose three extensions to these simulations: (i) we vary the sample size (N = {100, 500, 1000}) and the number of choice sets (T = {5, 10, 20, 50}), (ii) we estimate the models with both methods while deliberately omitting a variable that is in the data generating process, (iii) we introduce the socio-economic variables into the variance of the preferences, in order to simulate heteroscedasticity.

Second, we compare both methods using data from a real choice experiment on light pollution mitigation policy, in Montpellier Metropolitan Area (South of France). We predict the WTPs at the IRIS[1] scale, using data from the general census.

Results	***100 – 250 words***

The results of Monte Carlo simulations show that the one-step method performs much better than the two-step method, both in terms of parameter estimation and spatialization of the results. Regarding the estimation of the attribute coefficient, we find a mean average percentage error (MAPE) of 24,4%, versus 99,3% for the two-step method. This result is expected since the one-step method is fully consistent with the data generating process. The error is reduced when WTPs are predicted by geographic zone: we find a MAPE of 2,3% for the one-step method, versus 6,6% for the two-step method. However, predictions from the two-step method show very little variation between zones.

The one-step method continues to deliver increasingly superior performance as the number of observations N and the number of choice cards T increase, until reaching a MAPE for the predictions of 0.8% for N = 1000 and T = 50. For N = 100, the two-step method also performs better and better when T increases. However, for N = 500 and N = 1000, the MAPE remains stable (around 6.5%) for the two-step method, whatever

[1] In France, sub-municipal census tracts are called "IRIS" (*Illots regroupés pour l'Information Statistique*) and have a targeted size of 2000 inhabitants.

the values of T. In the case of omitted variable and heteroscedasticity, both methods predict WTP far from their true value and their MAPE are not significantly different.

Regarding the results of the case study, we observe slight variations in the significance of the coefficients, yet there is no inconsistency in the interpretation of the results. We find that the two-step method predicts much less widespread values, and much less negative or close-to-zero values than the one-step method. For one of the attributes, the one-step method predicts values that range between -170€ and 53€, while the two-step method's predictions range between -34€ and 49€. Plus, the two-step method predicts WTPs that are lower than zero for 4 geographic zones, versus 18 for the one-step method.

Discussion and Conclusion	***100 – 250 words***

Our findings indicate that the one-step method seems to be the best method to spatially predict preferences derived from a choice experiment, for several reasons. First, although we find a quite good MAPE for the WTPs predictions with the two-step method, this method predicts very little variation between zones in absolute value compared to the true WTPs. This result is true both for the Monte Carlo simulations and the case study, and can be a concern when it comes to guiding public decision-making as it makes it difficult to draw any conclusion on the spatial heterogeneity of preferences. Moreover, the one-step method seems to be more robust in general from a theoretical perspective, so it seems safer to use this method instead of the two-step method.

However, it is worth highlighting certain practical aspects of the two-step method compared with the one-step method, that can be of interest to applied researchers. Firstly, the two-step method takes much less time to run than the one-step method. For N = 1000 and T = 10, we observe that the one-step method takes 30% more time to run. This difference becomes increasingly important as we increase N, T or the number of parameters – so, in the case of the one-step method, the number of interaction variables. This gives the two-step method a second advantage over the one-step method: the former is much more flexible regarding the inclusion of control variables than the latter.

We therefore recommend to use the one-step method whenever possible. However, if the two-step method is more convenient to use, we advise caution when interpreting the results. More precisely, we advise to interpret the predicted WTP relatively to each other rather than in absolute value.