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The link between response time and preference, variance and processing heterogeneity in stated choice experiments

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ABSTRACT

In this article we utilize the time respondents require to answer a self-administered online stated preference survey. While the effects of response time have been previously explored, this article proposes a different approach that explicitly recognizes the highly equivocal relationship between response time and respondents' choices. In particular, we attempt to disentangle preference, variance and processing heterogeneity and explore whether response time helps to explain these three types of heterogeneity. For this, we divide the data (ordered by response time) into approximately equal-sized subsets, and then derive different class membership probabilities for each subset. We estimate a large number of candidate models and subsequently conduct a frequentist-based model averaging approach using information criteria to derive weights of evidence for each model. Our findings show a clear link between response time and utility coefficients, error variance and processing strategies. Our results thus emphasize the importance of considering response time when modeling stated choice data.

Introduction

When collecting stated preference data, online surveys have become more and more important and widespread. One reason for this is due to improvements in computer technology, but also the increased availability of the internet. Yet another reason for this increasing popularity stems from the fact that online surveys have a number of advantages over more traditional survey modes, such as mail-out paper-and-pen questionnaires, personal interviews and telephone interviews. Advantages typically mentioned in the resource economics literature (cf. Lindhjem and Navrud, 2011a, 2011b; Fleming and Bowden, 2009; Olsen, 2009) are reduced costs, increased speed of data collection, less item non-responses, ability to adjust questionnaires according to respondent answers on-the-fly, potential for broader stimuli in terms of graphics and sound, and avoidance of manual data entry mistakes. While advantages are many, this literature has also highlighted a few important potential disadvantages, which raise concerns regarding data quality and their suitability in non-market valuation (Lindhjem and Navrud, 2011a, 2011b). In particular, these disadvantages relate to problems concerning sample coverage and representativeness and self-selection bias. While not unique to online surveys, there can be so-called “pure survey mode effects”, whereby a respondent provides different answers to otherwise identical questions only because

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it is administered through different survey modes.

This article focuses on one aspect of online surveys—the length of time respondents take to complete the choice experiment. The concern is that, notwithstanding the fact, as pointed out by Cook et al. (2012), that online surveys allow respondents "time to think" and reflect, an interviewer is not present to pace the respondent. For this reason, some respondents may not exert the level of cognitive effort needed to answer the questions in any meaningful way. While this concern also applies to other self-administered methods of data collection, understanding the role of response time in online surveys is especially important because of the incentives that respondents often obtain for their continued participation in such surveys. Furthermore, as respondents within pre-recruited online panels gain experience, the tendency to answer quickly may actually increase (Malhotra, 2008). Consequently, with online surveys we may in fact increase the risks of panel attrition effects and surveying of experienced respondents—whose primary motivation for participating stems from the reward (either monetary or non-monetary) they receive—who answer so quickly that their choices do not reflect their actual preferences for the good in question. If this is indeed the case, there are obvious implications since it challenges the validity of any inferences made from the observed choices. Therefore, there may be reasons to be skeptical of "quick-and-dirty" responses, as coined by Schwappach and Strasmann (2006) and Olsen (2009), collected from online surveys in which participants are recruited and motivated by an incentive for completing the survey (Bonsall and Lythgoe, 2009). Similarly, concerns of reliability may be warranted for respondents who require significantly more time than would be reasonably expected. This could signal that these respondents faced distractions or were multitasking and, thus, did not give the choice decisions their utmost attention. In spite of these issues, this subject has yet to receive much attention, which gives rise to the present study.

Although the importance of response time has received considerable attention within experimental psychology, consumer research and marketing research (e.g., see Haaijer et al., 2000; Luce, 1986; Rubinstein, 2007), there are relatively few investigations within the stated preference literature (see Holmes et al., 1998; Haaijer et al., 2000; Rose and Black, 2006; Otter et al., 2008; Brown et al., 2008; Bonsall and Lythgoe, 2009; Vista et al., 2009; Hess and Stathopoulos, 2013; Börger, in press; Börjesson and Fosgerau, 2015; Campbell and Mørkbak, in press, for applications). Though, as can be seen from the above references, interest in this topic has clearly increased recently, and Bonsall and Lythgoe (2009) note that there is considerable scope for more research. Our article is intended to contribute to this area and provide a robust modeling framework for practitioners engaged in analyzing stated choice experiments. Unlike the articles mentioned above, which have established that response time has a significant bearing on the estimates of utility coefficients, error variance, model fit and predictions, we are interested in identifying the link between the length of time respondents require to answer the choice experiment and their preferences, variances and processing strategies (specifically, choice set generation) in a simultaneous estimation. While establishing the link between response time and any one of these types of heterogeneity is relatively straightforward, tackling all three simultaneously poses a challenge. Nevertheless, when only one type of heterogeneity is accounted for, there is a potential risk that the actual heterogeneity among respondents is only partially explained and, in fact, may actually be an artifact of another (unmodeled) type. For this reason, attempts to accommodate more than one type of heterogeneity at the same time would seem justified. In Campbell and Mørkbak (in press) we accommodate two types of heterogeneity, namely preference and variance heterogeneity, while leaving out any heterogeneity in the processing strategies adopted. With respect to response time, this latter type of heterogeneity seems highly relevant, in the sense that response time may be highly correlated with the use of any decision heuristic. Thus, in this article, while acknowledging the difficulty in separating the three types of heterogeneity simultaneously, we use latent class modeling to separately identify the different types of heterogeneity within the sample of respondents and to explore whether the class memberships differ by response time. This represents a step forward in the analysis of heterogeneity. This is the first article to explore the link between response time and processing strategies in the form of consideration set formation. Moreover, unlike Thiene and Scarpa (2015), who also disentangle three different types of heterogeneity, this is the first attempt to investigate the connection between each type of heterogeneity and response time.

In our earlier study (Campbell and Mørkbak, in press), which was based on a survey investigating recreational anglers' preferences for fishing sites, we set out to identify fast and slow respondents, but ended up concluding that identifying the thresholds is fraught with difficulty and, therefore, found no justification to drop respondents from the analysis on the basis of response time. In the present paper, we reiterate this conclusion but suggest a potential solution by approaching the issue from a different perspective. Rather than identify response time thresholds, this paper focuses on the differences between the respondents and we address the issue by not settling on an unique 'best' model, but instead 'averaging' over a bunch of models through the use of a multimodel inference approach. Our analysis is based on the division of the data (ordered by response time) into approximately equal-sized subsets. Crucially, for each subset we retrieve separate class sizes, which is fundamental for a meaningful investigation of response time. Under this framework, we are in a better position to distinguish the respondents who answered quickly and relatively inconsistently from those who also answered quickly but in a more consistent manner and, in the same vein, between respondents who took longer because they did not give the survey their full attention and those who took longer because they more fully evaluated the information presented to them. This is an important contribution of our work.

Our analysis considers 90 candidate model specifications to test for the number of preference classes, error variance classes, processing strategies and the number of different subsets based on response time. With so many competing model specifications, there is an inherent uncertainty of the true model. Given this uncertainty, and the fact that each of our different models provide different relative statistical fits, it does not seem sensible to ultimately select only one model.