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Discrete choice experiment response rates: A meta-analysis

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Abstract

Aims: Discrete choice experiments (DCEs) are used to elicit patients', the public's or health care professionals' preferences for health and health care. DCEs are a survey method and therefore are prone to survey error (coverage, sampling, non-response, and measurement error). While most DCE methodology papers focus on minimising measurement error, e.g. reducing hypothetical bias, improving question format/framing and refining econometric analysis, research focusing on non-response error in DCEs in healthcare is lacking. Most researchers aim to maximise a survey's response rate, which may reduce non response error. This study aims to add to the understanding of influences on response rates and tests the impact of various study design features on DCE response rates.

Methods and data: A systematic literature search for published DCE studies in healthcare updated an existing literature review for the period 2001 to 2008 to the end of 2011 and was used to identify the studies included in a meta-analysis. Studies resulting in more than one publication were included only once. Publications reporting results from more than one study were included as separate observations. For all identified studies we extracted the response rate and study

design information. Not all studies report all data, we have contacted authors to obtain the missing data.

The response rate is the dependent variable in our analysis. The explanatory variables are chosen based on explanations of survey response rates and hypotheses about how DCE study characteristics may affect response rates. Our modelling strategy takes account of several issues presented by the data generating process. The response rate variable is bounded between zero and 100%. Categorical explanatory variables are grouped based on a-priori hypotheses and number of observations in each category. We test for multicollinearity in these data by estimating pairwise correlations between variables. We allow that the error term may be correlated across studies that use the same questionnaire for data collection in different populations.

Preliminary results and conclusions: The search identified 371 papers from these we identified 306 studies that met the inclusion criteria. Preliminary data analysis indicates that response rates have been decreasing over time, in line with anecdotal evidence. DCEs with more attributes have lower response rates, as do studies eliciting time preferences. However, the number of choice sets and presence of a cost or risk attributes do not affect response rates. Response rates are lower from the general public than from patients and health care professionals.

*Keywords***:** discrete choice experiments, response rates, survey design

Introduction

Discrete choice experiments (DCEs) are widely used to elicit patients', the public's or health care professionals' preferences for health and health care (de Bekker-Grob et al, 2012). DCEs are a survey method, and are prone to several sources of error such as coverage error, sampling error, non-response error, and measurement error (Couper 2000, p466; Groves, 1989). Many research paper test how to minimise measurement error in DCE responses. For example, by reducing hypothetical bias (Özdemir et al, 2009), improving question format (Lancsar et al, 2013) or through a better understanding of how the DCE design affects responses (see for example Bech et al, 2011; and Ryan and Wordsworth, 2000). However, research on non-response error in DCEs in healthcare is lacking. We focus on this in our paper.

Non response error occurs when sampled individuals who do not respond to the survey are different in some important way from sampled individuals who do not respond. One way to minimise non response error is to maximise response rates by encouraging as many as possible of the individuals selected to take part in the survey to respond.[1] There exists an extensive literature on survey implementation that provides details on methods that can be used to improve survey response rates (Dillman et al, 2009). Dillman et al (2009) present a framework that considers survey responses to as a social exchange between the surveyor and the respondent. They assume that an individual will respond to an invitation to take part in a survey if they perceive that the benefits of responding to the survey will outweigh the costs. Dillman et al (2009) use this framework to make recommendations about generic aspects of survey design, such as the survey presentation and lay-out, the invitation letter, etc. However, the notion of social exchange can be used to consider how DCE specific survey features may also affect response rates.

In general, a respondent completes a voluntary survey because of the reward that they perceive their action will bring from others (Dillman, 2009). This framework can be used to consider why individuals will respond to an invitation to complete a

[1] Increasing the response rate also has the advantage of reducing data collection costs by reducing the number of surveys that need to be administered to achieve a target sample size.

health care DCE survey. The perceived benefits of completing the survey will depend on the study context. For example, in a study of patients' preference for health care treatments for their illness, patients' perceived benefits of responding to the survey may include the possibilities that their response leads to improvements in their future health care treatment, and/or improvements in treatment for others with the same illness. The perceived benefits of responding to the survey will differ depending on the population is asked to complete the questionnaire (general public, patients, health care professionals) and the good preferences are being elicited for (treatments, screening tests, service provision, health care professional work contracts).

The perceived costs of responding to a health care DCE survey will depend on many survey design features and will be positively linked to the cognitive burden that completing the survey places on respondents (Presser et al, 2004). Several studies have investigated how different aspects of a DCEs design affect the cognitive burden to respondents of completing the task. The cognitive burden is found to be increasing in the number of attributes and number of alternatives in a choice set, and in the number of choice sets respondents are asked to complete (Mazzota and Opaluch, 1995; Swait and Adamowicz, 2001; DeShazo and Fermo, 2002). Bryan et al (2001) find higher item non-response and Pedersen et al (2011) find higher model variance when comparing DCEs with and without a cost attribute. These results indicate that presence of a cost attribute may increase the cognitive burden of the task. Furthermore, it is known that patients and the general public struggle to understand the concept of risk (Lloyd, 2001). Consequently, including risk attributes in a DCE may increase the cognitive burden.

The above studies have focussed on how cognitive burden affects the quality of data provided (measurement error); here we argue that the cognitive burden will also affect whether sampled individuals will respond to the task. Related to this, Bech et al (2011) investigate the impact of the number of choice sets presented to respondents in a DCE on response rates. They compare response rates (and other measures) across the same online DCE survey about dental health care administered to the Danish population that differs only in the number of choice

sets (5, 9 or 17 choice sets). They find no difference in response rates across survey versions. This is in line with the findings of Hensher et al (2001) and Stopher and Hensher (2000) for DCE concerned with transportation.

This paper tests how various aspects of DCE study design affect response rates. To do this, we use a meta-analysis of all published applied DCE studies in healthcare between 2001 and 2011. Section 2 discusses the study design including the methods used to identified published applied DCE studies in healthcare, the data extracted from the published studies and the meta regression analysis of the resulting data set. Section 3 presents the results of our meta regression analysis and Section 4 discusses these results and their implications for DCE study design in healthcare.

2. Methods

We used a meta regression analysis to investigate the impact of various aspects of DCE study design on survey response rates. Meta regression analysis is a statistical analysis that combines results from different independent studies (Glass, 1976; Huque 1988). It overcomes the limitations of a single study by considering heterogeneity between the observed study results in the analysis, and thus allows for more profound insights in to the variation of findings. In health care studies, meta regression analyses are usually used to pool results from a set of related randomized control trials (RCTs), thus increasing the sample size and the statistical power to detect an effect of interest. Meta regression analyses have also been used to measure time preference rates (Asenso-Boadi et al, 2008) and the value of a statistical life (Johnson et al, 1997). Several meta regression analyses of stated preference studies valuing non-market goods have been published. Mostly these studies pool willingness to pay (WTP) values from across different studies that valued the same or similar goods for the purpose of benefits transfer (Lindhjem and Navrud, 2008; Barrio and Loureiro, 2008).

A smaller number of studies have used meta regression analysis to test methodological issues related to the applications of stated preference methods. For

instance, List and Gallet (2001), Little and Berrens (2004) and Murphy et al (2005) conduct meta regression analyses to compare how study design features affect the magnitude of hypothetical bias across contingent valuation studies. Our paper is similar in spirit to these studies.

We combined evidence from individual applied DCE studies in health care in order to gain a better understanding of the factors that affect survey response rates. The first stage in any meta regression analysis is to identify the studies that are included as observations in the data set. We did this using a systematic literature review. After eligible studies were identified we extracted information about the main variables of interest to use as explanatory variables in our meta regression analysis. The systematic literature review and data extraction are detailed below.

2.1. Data description

The systematic literature review combined an existing systematic literature review for the period 2001 to 2008 (de Bekker-Grob et al, 2012) with a systematic review to the end of 2011. The search terms used in the systematic review were the same as those used by Ryan and Gerard (2003) and de Bekker-Grob et al (2012): discrete choice experiment(s), discrete choice model/models/modelling, discrete choice method(s), discrete choice study, stated preference(s), part-worth utilities, functional measurement(s), paired comparison(s), pairwise choice(s), conjoint analysis/analyses, conjoint study/studies, conjoint measurement(s), conjoint approach, conjoint choice experiment. We searched the following databases: MEDLINE; EMBASE; HEALTHSTAR; Social Science Citation Index; PsychLIT; EconLIT; and Health Management Information Consortium. In order to overcome potential indexing problems in the databases, we also conducted a hand search of key journals and checked reference lists of obtained papers[2].

[2] We cross checked our review with another literature review being carried out at the same time by Drs Karen Gerard and Tim Bolt.

Following de Bekker-Grob et al (2012) studies were included if they asked respondents to complete choice-based DCE tasks[3], were published in English and were published as a full-text article. Some studies result in more than one journbal article/publication from the same data set; in this case, we include the study only once in our data set and take the first published paper as the date of publication. Some publications report the results from more than one study. For example, for our purpose we consider the same questionnaire administered to two different populations or different questionnaires administered to subgroups of the same population to be different studies; in these cases we included these as separate observations in our data set.

To build a data set for the meta regression analysis required that we extract the data of interest from the identified published papers. If the required data were not included in the papers, we contacted the corresponding author of the paper by email to request the missing information. The estimate of interest in our meta regression analysis is the survey response rate. For all identified studies, we extracted, when possible, both the response rate and the usable response rate. The usable response rate is the response rate based on the number of respondents that are included for DCE analysis (e.g., several researchers remove respondents who failed rationality checks, or failed to fill in all DCE questions, etc. If it was not clear whether the response rate reported was the response rate or the usable response rate we contacted the corresponding author to clarify. Furthermore, the identified studies were classified using the criteria of de Bekker-Grob et al (2012). This classification sorted the studies according to broad categories of the type of good being valued and the objectives of the study. There are eight categories: 1) Patient experience valuation; 2) Health outcome valuation; 3) Trade-offs between health outcomes and patient experiences; 4) Estimating utility weights within the QALY framework; 5) Investigating labour-market choices amongst health professionals; 6) Developing priority setting frameworks; 7) Clinical decision making; 8) Other.

We extracted study design information to use as explanatory variables in our meta regression analysis. The explanatory variables are chosen based on general theories about why individuals respond to surveys and hypotheses about how DCE

[3] We exclude ranking and rating conjoint tasks and also adaptive conjoint analysis.

study characteristics affect the cognitive burden that respondents face. Therefore, the explanatory variables relate to aspects of the DCE design, the survey design, and other general study characteristics.

We extract data on seven DCE study characteristics that affect the effort required by respondents to complete the task: the number of attributes in the DCE; the number of alternatives in each choice set; the number of choice sets each respondent was asked to complete; whether respondents were given the possibility to reject the hypothetical alternatives on offer by being offered an opt-out alternative (neither, status quo, or do nothing alternative); whether the DCE included a cost attribute to allow calculation of willingness to pay or accept; whether at least one of the attributes expressed a risk or probability; whether the DCE elicited time preferences; whether the same hypothetical alternative appears in all choice sets respondents answer – a so called constant comparator experimental design.

We extracted data on three other aspects of the survey design that may be expected to affect either individual's perceived benefit from responding to the survey or the effort required of them. First, we recorded if reminders were sent to non-respondents. Second, we recorded the study sample to distinguish between studies eliciting the preferences of patients, spouse/parents/informal carers, health care professionals and the general population. Third, we recorded the survey administration mode to distinguish between self-complete and interviewer administered surveys, we further distinguished between postal self-complete surveys and those completed by patients in a clinic waiting room; we also record if the survey was administered online.

We also extracted data on general characteristics of the study that may affect response rates. We recorded the disease area or condition that was the focus of the study and distinguished between studies eliciting preferences for aspects of patients' experiences, for health outcomes, or both. The acceptability of valuing and trading off these different benefits may influence the studies response rate. We distinguished between studies based on the perspective respondents are asked to express in their preferences. Specifically, we distinguished between studies

eliciting respondents' individual preferences, eliciting health care professionals' preferences on behalf of patients, and individuals' preferences on behalf of others in society.

We also extracted a set of other data that can be used to control for response rate heterogeneity not explained by study characteristics. Specifically, we recorded the country in which the data were collected and the publication year as a proxy for the date the study was carried out.

2.2. Data analysis

The dependent variable in our meta analysis is a vector of survey response rates (not usable response rates) from the i studies, y_i . The explanatory variables are grouped into four categories – the DCE's characteristics, X_{DCE}, other survey characteristics, X_{SUR}, general study characteristics, X_{STU}, control variables, X_{CON}. The estimation model can be expressed by the following equation:

$$y_i = \alpha + X_{DCEi}\beta_{DCE} + X_{SURi}\beta_{SUR} + X_{STUi}\beta_{STU} + X_{CONi}\beta_{CON} + \varepsilon_i \quad (1)$$

where α is a constant term, the β vectors are the coefficients to be estimated for the explanatory variables, and ε is the residuals. We consider that each study counts equally in the data[4]. We estimate equation (1) using an ordinary least squares (OLS) estimator. In some cases, more than one study uses the same questionnaire for data collection in different populations. For example, the same questionnaire is administered to patients and health care professionals. Similarly, marginally different versions of a questionnaire will be administered to sub samples of the same population. For example, the same questionnaire is administered with 8 choice sets and 16 choice sets. In these cases, the error terms will be correlated leading to auto-correlation. Autocorrelation would lead to biased estimates of standard errors. To correct for this, we estimate equation (1) using a cluster robust

[4] Many meta regression analysis reweight using the variance of the measure of interest to account for uncertainty around the measure in the original study. In our case, this is not possible because we do not know the variance of the response rates. Future work will explore reweighting using sample size.

estimator of variance that relaxes the assumption that the error term in equation (1) is independent across all studies.

Meta regression analysis can be very sensitive to outliers and lack of variability in the data. We bear in mind issues of data variability and multicollinearity when specifying the explanatory variables in our regression equation. When grouping categorical variables we first group based on a-priori hypotheses about how these variables affect response rates, we then check the number of observations in each category and merge comparable categories where necessary. We test for multicollinearity in these data by estimating pairwise correlations and use a correlation of 0.7 or greater as an indicator that two variables are collinear.

3. Results

The data set available for the meta regression analysis includes 114 unique studies based on those identified by de Bekker-Grob et al (2012) for 2001-2008. A systematic literature review search for papers published between 2009 and 2011 identified 371 papers of which 306 papers met the inclusion criteria. From these 144 unique studies were identified, resulting in a total of 258 unique studies for 2001-2011. Some studies are excluded from analysis because of missing data on key variables of interest. This reduces our sample size for analysis to 171 unique studies.

When specifying equation (1) to explain variation in response rates across studies, there was no a-priori reason to expect that the explanatory variables would affect all survey modes in the same manner. Figure 1 summarises the use of each mode. We restrict the analysis in this paper to consider only postal surveys for four reasons. First, Interview administered questionnaires provide the respondent with the support of the interviewer to complete the questionnaire. Second, on starting online surveys to magnitude of the task ahead is often unclear. For these reasons, we hypothesize that the effect of survey cognitive burden would higher if surveys were postal questionnaires compared to interview administered or online surveys. Third, calculating response rates for online data collection modes is complicated. Fourth, asking individuals to complete the questionnaire when they are waiting at

a clinic or other central location is a prevalent mode (20% of all studies), many researchers did not record response rates for this mode. Therefore, this reduces the sample size to 93. The characteristics of all postal studies are presented in Table 1.

Table 2 presents the results from the meta regression analysis. From the results, we find that studies presenting participants with more attributes in the scenario description have lower response rates. Similarly, studies including 3 alternatives in a choice set have significantly lower response rates compared to those with only 2 alternatives. Compared to the reference category of 3-7 choice sets, response rates are significantly lower only for DCEs with 8 choice sets. Studies including an opt-out option in the DCE or at least one risk attribute have higher response rates. Studies eliciting time preferences have lower response rates. However, inclusion of a price proxy or using a constant comparator design does not appear to affect survey response rates.

With respect to aspects of the survey design the use of one or more reminders is found to increase the response rates significantly. Response rates are significantly higher in studies that draw their sample from patients or health care professionals compared to studies that draw a sample from the general public. We control for when the study was undertaken using the year of publication. Since 2001, response rates to postal surveys have been decreasing over time, in line with anecdotal evidence.

4. Discussion

We explore factors that affect response rates to health care DCE surveys using meta-regression analysis. Our results support our hypothesis that response rates are negatively related to survey cognitive burden. We find that response rates are lower when studies include more attributes and more alternatives per choice set. In line with Bech et al (2011) we find weak evidence of an effect of the number of choice sets on response rates. We find that response rates are higher when studies have an opt-out but that the presence of a price proxy does not affect responses. We also find evidence that response rates are linked to the perceived benefits to

respondents of responding to the survey. We find that surveys of patients and health care professional had higher response rates than those of the general public.

This paper found that response rates have been decreasing over time. DCEs with more attributes have lower response rates, as do studies eliciting time preferences. However, the number of choice sets and presence of a cost or risk attributes do not affect response rates. Response rates are lower from the general public than from patients and health care professionals.

There are two main limitations of this meta regression analysis. First, AAPOR publish guidelines for the calculation of response rates. It is unclear whether the response rates reported in many cases adhere to AAPOR guidelines. Where possible we rely on the response rates reported in the paper. Health care DCE studies collecting data on patient or public preferences for health and health care have typically used mail surveys sent to a random sample of the general population, or self-complete questionnaires distributed in clinics to a convenience sample of patients. There is also a belief that response rates to mail surveys have been decreasing over time, which also increases the cost of obtaining a sufficiently large sample sizes. More recently, researchers have used internet surveys of online panels to collect data as a solution. While response rates are reasonably easy to calculate for mail surveys they are difficult to calculate for online panels. Participation rates are an alternative measure that may provide some useful information, and are often reported as response rates for internet surveys. For internet surveys, participation rates will be calculated as the number of responses as a proportion of email invitations sent (less bounced emails). Another measure of participation is the number of responses as a proportion of the number of people who click on the link to view the questionnaire. Response rates for an internet survey using a probability-based panel are calculated by combining the participation rate with the response rate to the invitation to join the panel. Response rates are often unavailable for convenience samples because researchers do not always record the number of invitations to participate in the study.

Second, the potential of meta-analysis to improve the evidence base for treatment effects depends on the quality of the included studies and how quality variation is

controlled for in the analysis (Nelson and Kennedy, 2009). In this study, DCE response rates will be correlated with the quality of the original study, however, we do not include a measure study quality except through the ability of our regressors to capture this. The checklists for quality assessment usually applied in meta analyses of randomised control trials for e.g. economic evaluations (Evers et al, 2005) are not applicable to DCE studies, and there is no scientifically defensible way to turn existing DCE checklists into quality measures (Lancsar and Louviere, 2009). Furthermore, the survey quality in general as well as the DCE quality will affect response rates. Respondents' burden from completing the questionnaire will be affected by how well the questionnaire is worded, the total number of questions included, the repetitiveness of these questions, etc (Presser et al, 2004). Related to this, is the concern about publication bias that is inherent in all meta analyses (Nelson and Kennedy, 2009). Publication bias will result in a selection bias if included studies are less likely to be published or even submitted for publication when the response rates are low. This is similar to the selection bias potentially present in traditional meta analysis where papers that find insignificant or weak results are less likely to be published. Several papers have proposed methods to account for this selection (Hoehn, 2006; Sutton, 2000). We will explore the application of these corrections in our context.

Points for discussion

These are particular issues that we are grappling with in our data analysis at the moment:

1. Can we accounting for differences in study quality across the included studies given the information typically available in published papers? Even if we can do this will be still have a publication bias?
2. Each study counts equally – should we re-weight by sample size as a proxy for precision of response rate measure?
3. Response rates, and therefore the dependent variable, are bounded between zero and 100%. We plan to explore other estimators such as the TOBIT or others for fractional response variables (Papke and Wooldridge, 1996).
4. How to explore response rates across all modes – a meta analysis for each?

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References

Asenso-Boadi, F. Peters, T. and Coast, J. (2008). Exploring differences in empirical time preference rates for health: An application of meta-regression. *Health Economics*, 17, 235-248.

Barrio, M. Loureiro, M. (2010). A meta-analysis of contingent valuation forest studies. *Ecological Economics*, 69, 1023-1030.

Bech, M. Kjaer ,T. Lauridsen, J. (2011). Does the number of choice sets matter? Results from a web survey applying a discrete choice experiment. *Health Economics*, 20, 273-286.

Bryan, S. Buxton, M. Sheldon, R. Grant A. (2001). Magnetic resonance imaging for the investigate of knee injuries: an investigation of preferences. *Health Economics*, 7, 595-603.

de Bekker-Grob E, Ryan M, Gerard K, (2012). Discrete choice experiments in health economics: a review of the literature. *Health Economics,* 21, 145-172.

DeShazo, J.R. and Fermo G. (2002). Designing choice sets for stated preference methods: The effects of complexity on choice consistency. *Journal of Environmental Economics and Management*. 44, 123-43.

Dillman D. et al (2009). *Internet, mail and mixed-mode surveys: The tailored design method*. New Jersey, Wiley.

Evers S, Goossens M, de Vet H, van Tulder M, Ament A: Criteria list for assessment of methodological quality of economic evaluations: Consensus on Health Economic Criteria. *Int J Technol Assess Health Care 2005*; 21: 240–245.

Glass, G. (1976). Primary, secondary and meta analysis of research. *Education Research*, 10, 3-8.

Groves, R.M. (1989) *Survey Errors and Survey Costs*. Wiley: Philidephia

Hensher, D. Stopher, P. Louviere, J. (2001). An exploratory analysis of the effect of numbers of choices sets in designed choice experiments: an airline choice application. *Journal of Air Transport Management*. 7, 373-379.

Huque MF. (1988). Experiences with meta-analysis in NDA submissions. *Proceedings of the Biopharmaceutical Section of the American Statistical Association,* 2:28-33.

Johnson, F.R., Fries, E. Banzaf, H.S. (1997). Valuing morbidity: An interation of the willingness-to-pay and health-status index. *Journal of Health Economics*, 16, 641-665.

Lancsar E, Louviere J, Donaldson C, Currie G, Burgess L. Best Worst Discrete Choice Experiments in Health: Methods and an Application. *Social Science and Medicine*, 2013, 76: 74-82.

Lancsar E, Louviere J, (2009). Conducting Discrete Choice Experiments to Inform Healthcare Decision Making: A User's Guide. *PharmacoEconomics*, 26, 661-677.

Lindjem, H. Navrud, S. (2008). How reliable are meta-analyses for international benefit transfers? *Ecological Economics*, 66, 425-435.

List, J. Gallet, C. (2001). What Experimental Protocol Influence Disparities between Actual and Hypothetical Stated Values? *Environmental and Resource Economics,* 20, 241-254

Little, J. Berrens, R., (2004). Explaining disparities between actual and hypothetical stated values: further investigation using meta-analysis. *Economics Bulletin,* 3, 1-13.

Lloyd A. (2001). The extent of patients' understanding of the risk of treatments. *Quality in Health Care*, 10 suppl 1: i14-i18.

Mazzotta, M. Opaluch, J. (1995). Decision making when choices are complex: A test of Heiner's hypothesis. *Land Economics*, 71, 500--515.

Murphy, J. Allen, P. Stevens, T. Weatherhead D. (2005). A Meta-analysis of Hypothetical Bias in Stated Preference Valuation. *Environmental and Resource Economics,* 30. 313-325.

Nelson, J. Kennedy, P. (2011). The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment. *Environmental and Resource Economics*, 42, 345-377.

Özdemir S, Johnson FR, Hauber AB. (2009) Hypothetical Bias, Cheap Talk, and Stated Willingness to Pay for Health Care. *Journal of Health Economics*. 28, 894-901.

Papke, L/ Wooldridge, J. (1996). Econometric methods for fractional response variables with an application to 401(K) plan participation rates. *Journal of Applied Econometrics*, 11, 619-632.

Pedersen, L. Kjaer, T. Kragstrup, J. Gyrd-Hansen, D. Does the inclusion of a cost attribute in forced and unforced choices matter? Results from a web sruevy applying the discrete choice experiment. *Journal of Choice Modelling*. 4, 88-109.

Presser, S. Rothgeb, J. Couper, M. Lessler, J. Martin, E. Martin, J. Singer, L. (2004). *Methods for testing and evaluating survey questionnaires*. Wiley.

Ryan M, Gerard K. (2003). Using discrete choice experiments to value health care programmes: current practice and future research reflections. *Applied Health Economics Health Policy* 2: 55–64.

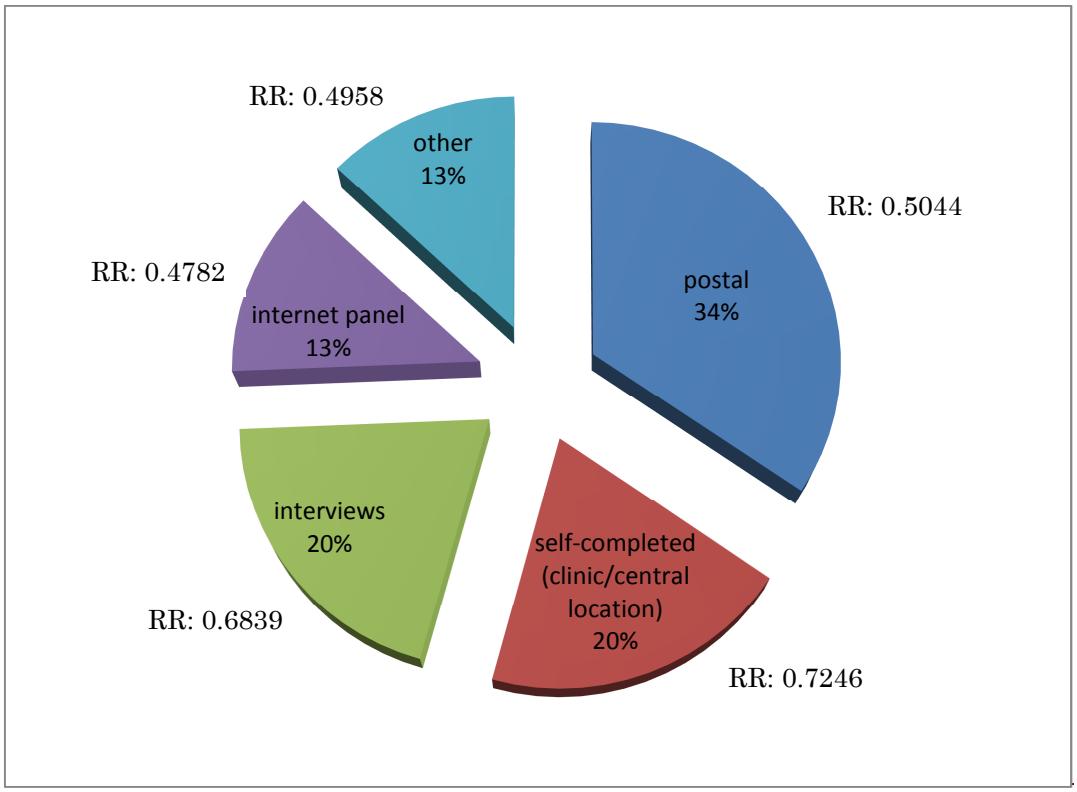
Ryan M, Wordsworth S. (2000). Sensitivity of willingness to pay estimates to the level of attributes in discrete choice experiments. *Scottish Journal of Political Economy* 47, 504-524.

Stopher, P. Hensher, D. (2000). Are more profiles better than fewer? Searching for parsimony and relevance in stated choice experiments. *Transportation Data, Statistics and Information Technology*. 1719, 165-174.

Swait, J. Adamowicz, W. (2001). The influence of task complexity on consumer choice: A latent class model of decision strategy switching. *Journal of Consumer Research*. 28, 135-48.

Swait, J. Adamowicz, W. (2001). Choice environment, market complexity and consumer behaviour: A theoretical and empirical approach for incorporating decision complexity into models of consumer choice. *Organizational Behavior and Human Decision Processes*. 86, 141-167.

Figure 1: Proportion of studies and mean response rate (RR) by survey mode (N = 269[5])



[5] The number of studies is different from the one mentioned in the results section (i.e. n=258) because some of the unique studies would use different survey administration methods in different versions of the questionnaire.

Table 1: Characteristics of included studies (postal surveys only, n=93)

Variables		**Summary statistics**	
		%	*Mean (Standard deviation)*
Design variables			
Number of attributes			5.30 (1.99)
	2-4 attributes*	0.31	
	5 attributes	0.23	
	6 attributes	0.28	
	7-8 attributes	0.15	
	>8 attributes	0.03	
Number of alternatives			2.56 (1.74)
	2 alternatives*	0.63	
	3 alternatives	0.30	
	>3 alternatives	0.06	
Number of choice sets			12.21 (17.39)
	No. of choice sets: 3-7*	0.24	
	No. of choice sets: 8	0.17	
	No. of choice sets: 9-15	0.31	
	No. of choice sets: 16	0.15	
	No. of choice sets: >16	0.11	
Opt-out option		0.32	
Price proxy		0.44	
Risk attribute		0.39	
Time preferences		0.21	
Constant comparator			
Study variables			
Population	General public*	0.20	
	Patients and carers	0.52	
	Health care professionals	0.22	
	Other	0.07	
Perspective	Own*	0.80	
	Other	0.21	
Reminder	0*	0.08	
	1+	0.83	

** indicates the reference group for the analysis.*

Table 2: Meta analysis results using OLS estimator (n=93)

Variables		Coefficient ß	Significance[6]	Robust SE
Design variables				
Number of attributes	2-4 attributes			
	5 attributes	-15.46	*	8.78
	6 attributes	-19.48	**	7.40
	7-8 attributes	-21.71	***	7.62
	>8 attributes	-28.57		20.24
Number of alternatives	2 alternatives			
	3 alternatives	-30.08	***	11.23
	>3 alternatives	-31.79		28.97
Number of choice sets	No. of choice sets: 3-7			
	No. of choice sets: 8	-28.98	***	9.89
	No. of choice sets: 9-15	-10.47		7.50
	No. of choice sets: 16	-21.76		13.99
	No. of choice sets: >16	-5.82		9.32
Opt-out option		26.41	***	8.90
Price proxy		-4.74		7.69
Risk attribute		7.79	*	4.46
Time preferences		-16.70	*	9.69
Constant comparator		-1.09		5.89
Study variables				
Population	General public			
	Patients and carers	32.15	***	6.13
	Health care professionals	24.98	**	10.13
	Other	8.05		13.64
Perspective	Own			
	Others'	-9.42		7.68
Reminder		2.31	**	1.01
Control variables				
Country	UK			
	US	2.56		12.67
	Australia	4.84		9.34
	Canada	4.39		13.78
	Netherlands & Belgium	1.89		10.13
	Scandinavia/Nordic countries	19.33	*	10.92
	Rest of Europe	-31.64	**	12.51
	Western Pacific region	20.00		19.74

[6] *** at 1% level, ** at 5% level, * at 10% level.

Variables		Coefficient ß	Significance[6]	Robust SE
Year of publication	2001			
	2002	-7.62		10.84
	2003	-20.41		12.25
	2004	-24.01	*	12.35
	2005	-14.77		15.52
	2006	-1.20		9.72
	2007	-10.53		8.97
	2008	-16.83		11.01
	2009	-25.31	*	14.56
	2010	-0.54		15.33
	2011	-20.19		13.59
	2012	-0.88		24.39
_cons		74.98	***	16.84
R2		*0.7469*		