# Appendix 1. Information on experimental design and statistical analyses

## Experimental design

By minimizing the D-efficiency criterion, a main-effects efficient Bayesian design based on best guess priors was generated using Ngene software (Choice Metrics, version 1.1.1.). These priors (small positive and negative values) were used to increase the efficiency of the design by avoiding dominant choice sets. We created a design with 12 choice sets to ensure enough degrees of freedom to estimate all main effects (assuming a non-categorical cost attribute), in which also level balance was achieved. This experimental design was used in the pilot study. Afterwards, priors, derived from pilot test data using a multinomial logit model, was used to generate the final experimental design.

## Statistical analyses

To estimate utilities, we used a random utility theory framework where the true but latent utility for alternative *i* of individual *n* can be written as:

(1)

*Vin* represents the observable systematic component of utility, which is the explainable proportion of the choice of alternative *i* of individual *n*, and *εin* is the non-explainable proportion representing the unobservable and random treated component. Assuming a linear additive utility function, the observable component for individual *n* for alternative *i* becomes  where is a vector of attributes. The linear predictor, *V*, of the applied models is shown below.

(2) *Vin = αi + β1stor1in + β2stor2in + β3stor3in + β4tech1in*

*+ β5tech2in + β6tech3in + β7data1in + β8use1in + β9costin*

Where  refers to the alternative specific constant (ASC) appropriate for that split. In the split where both a status quo and an opt-out are included, two ASCs were estimated. In that case,  is the sum of the estimates for the two constants.

Assuming that the error terms are independent and identically distributed (iid) extreme value random variables, makes a logit model appropriate. Assuming that the coefficients vary over respondents with density, a mixed logit random parameters model can be specified which also takes account of the panel structure in the data and relaxes the independence of irrelevant alternatives (IIA) assumption. The probability of choosing alternative *i* for individual *n* is given by:

(3) 

Where  is the scale parameter, which is inversely related to the error variance (1).

We use an error component specification, by specifying the ASC(s) as random and decompose them into mean and deviation  such that

(4) 

All other parameters are held fixed. Error component models were estimated in Stata (version 14), using the ‘mixlogit’ command using 1000 Halton draws (2).

Individual status quo levels were incorporated in the analysis for research question 2. In all models the attributes (except the cost attribute) were effects coded (3) to enable the interpretation of the estimates for the ASCs. Marginal utilities were calculated afterwards and presented in the tables in the results section. Different functional forms for the cost attribute were tested in all splits (linear, log linear, quadratic and square root transformations), and a linear form was chosen as model fits (AIC and BIC) showed that this was just as good as or better than the other functional forms tested. We only included an ASC for the opt-out/neither/ status quo alternative since there was no left-right bias for the hypothetical scenarios in any of the splits.

**References**

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3. Bech M, Gyrd-Hansen D. Effects coding in discrete choice experiments. Health Econ. 2005;14(10):1079-83. doi: 10.1002/hec.984. PubMed PMID: 15852455.