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Capturing zero-price effects in stated choice surveys: implications for willingness-to-pay and welfare

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Abstract: Stated choice surveys commonly used in public policy appraisal – such as in transport or environmental economics – often contrast a 'free' status quo alternative against a range of (policy) interventions which can be implemented at a cost. Limited attention has, however, been paid to the fact that the 'free' nature of the status quo (SQ) alternative may make the SQ alternative overly attractive due to the zero-price (ZP) effect. The ZP effect is a well-established notion in behavioural economics explaining the phenomenon that individuals tend to over-react to free alternatives. We present an experimental design setup allowing the separation of the ZP effect from the SQ effect together with the identification of non-linear sensitivities to costs. Choices made by students between different mobile broadband packages are used for illustrational purposes. Our analysis shows that the ZP effect is significant and the observed preference to remain in the SQ is largely due to the ZP effect. In practice, this may lead to biased welfare estimates for public policy packages if the ZP effect is not explicitly accounted for. Moreover, we also show that misspecification of the functional form for cost can lead to significant bias in WTP estimates and the ZP and SQ effects.

Keywords: zero-price effect, stated choice experiments, status quo bias, willingness-to-pay, welfare analysis, discrete choice modelling, non-linear cost sensitivity, Box-Cox transformation, mobile broadband

JEL codes: C25, D91, D61, Q51, L96

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1. Introduction

Stated choice (SC) surveys are used extensively to forecast demand and capture welfare effects of policy changes (Louviere et al. 2000; Ben-Akiva, McFadden, and Train 2019). While it is a common practice to apply random utility maximisation (RUM) models for analysing choice behaviour based on SC data (McFadden 1986; Carson and Louviere 2011), there has been a growing interest in behavioural phenomena that can imply departures from the RUM framework (Hess, Daly, and Batley 2018; Hensher 2019; Chorus and Van Cranenburgh 2024).

Amongst these alternative behavioural phenomena, a well-established notion in behavioural economics is that individuals tend to get over-attracted to free alternatives. This psychological mechanism was coined as the zero-price (ZP) effect (Shampanier, Mazar, and Ariely 2007; Ariely 2008). The ZP effect has been demonstrated in many different forms. Some examples include the choice of chocolate brands (Shampanier, Mazar, and Ariely 2007), hotel room bookings in a two-component setting where the breakfast could be free (Nicolau and Sellers 2012), pseudo-free offers where nonmonetary payments (e.g. time, personal information, privacy) are included as cost components (Dallas and Morwitz 2018), access to e-services (e.g. music/video streaming services) that could be free (Hüttel et al. 2018), and premiums to health insurance which are subsided by public money (Douven et al. 2020). Hossain and Saini (2015) conducted a series of experiments using between-subject designs and found that the relative preference for hedonic products is disproportionately enhanced when they are offered for free, compared to utilitarian products. They argued that this can be explained by the affect-rich nature of hedonic stimuli, which trigger a more concave, non-linear evaluation of price. More recently, Zhang et al. (2023) provided evidence, through a discrete-choice experiment, that individuals tend to prefer a hotel offering one free night, and that free pricing has a greater impact on shifting preferences than a nominal price.

Despite a wealth of evidence of the ZP effect in the behavioural economics literature, the non-market valuation literature has paid very little attention to this phenomenon. In fact, Hanley et al. (2001) make a strong argument to include a '*status quo*' (SQ) or '*do nothing*' scenario in the choice set in order to link the choice set with the respondent's current feasible choice set and therefore interpret the results in terms of welfare economics. The SQ alternative is, however, nearly almost always presented as a zero-cost option, which in the presence of the ZP effect may make it overly attractive. The lack of explicit treatment of ZP effect in discrete choice applications therefore creates significant risks in producing biased parameters and welfare measures leading to inferior policy recommendations.

Researchers have conducted in-depth analyses of the over-reaction towards the SQ alternative, also referred to as the SQ effect/bias (Samuelson and Zeckhauser 1988). This includes improving the understanding of the behavioural rationale (Meyerhoff and Liebe 2009; Adamowicz et al. 1998; J. Zhang and Adamowicz 2011), addressing econometric issues regarding model specifications for the SQ effects (Scarpa, Ferrini, and Willis 2005; Oehlmann et al. 2017), and identifying impacts of SQ effect to the welfare analysis (Adamowicz et al. 2011). Nevertheless, the ZP effect has rarely been mentioned as a possible behavioural cause for the SQ effect, despite its perfect confounding (see discussion in Hess and Beharrry-Borg (2012)).

Our objective is to assess whether the attractiveness of the SQ alternative typically observed in SC studies is largely due to the ZP effect. To this end, we develop a specific study design, where the SQ option is associated with small costs in some choice cards. This paper also identifies requirements for capturing the ZP effect in isolation of non-linear cost sensitivities (Daly 2010; Rich and Mabit 2016). We show that to separate the ZP effect from non-linear cost sensitivity small costs levels need to be incorporated in the experimental design. We focus on the impact of these design features on WTP and compensating variations calculations, as well as the relationship between ZP effects, non-linearity in cost sensitivities and SQ effects. We specifically look at choices made by students between different mobile broadband packages. We chose this context to ensure that survey subjects are familiar with the products or designed policies and can thus be expected to make similar decisions as in reality (Ben-Akiva, McFadden, and Train 2019). Notably, with this study design we aim to overcome some of the shortcomings found in Hess et al. (2018) who highlight that it is possible to capture ZP effects without abandoning the RUM framework, but that this comes at the risk of obtaining extreme welfare measures. Whilst we recognise that SC contexts vary across domains – for instance, in non-market valuation studies where respondents are often unfamiliar with the goods or with paying for them – our study serves as a proof of concept under controlled conditions. The zero-cost status quo and paid alternatives reflect a design structure common to many SC applications, allowing us to isolate the zero-price effect without additional complexity arising from product unfamiliarity. This provides a foundation for future research in more abstract or less familiar policy domains.

The remainder of the paper is structured as follows. **Section 0** describes the experimental setup. **Section 0** outlines the research methodology. **Section 0** summarises the model results from the SC data. Lastly, **Section 0** discusses policy implications and concludes.

2. Experimental setup

2.1. Design *overview*

Our experiment draws on SC data collected from 302 students at the University of Warsaw (Poland) in late 2017. Respondents are asked to choose between retaining the free campus-wide Wi-Fi service (i.e., the SQ alternative) or to purchase a 4G LTE data package which offers access to high-speed mobile data beyond the school campus by using a USB dongle. Three attributes are varied amongst choice tasks: monthly costs of the 4G LTE data package and the campus-wide Wi-Fi service; monthly data download limit; and the number of devices that can simultaneously share the bandwidth. The cost levels of the 4G LTE data package are set to be lower than commercial packages typically offered by the major mobile network operator to make the trade-offs more plausible and engaging for students to consider the presented mobile data packages. Prior to the stated choice tasks, respondents answer a few basic questions concerning current internet usage experience, and their existing mobile data contracts.

This experiment is characterised by 3 different treatments. The first treatment (SP1) mimics a common format of choice sets, including a SQ alternative with zero price and two experimentally designed alternatives (e.g., the standard '2+*SQ*' format as described in Ferrini and Scarpa (2007), often applied in environmental economics). We also acknowledge that this structure is not universally used across all stated choice contexts; for instance, many stated choice applications in health economics adopt two-alternative designs, with the status quo option included less consistently (Soekhai et al., 2018). This difference in format raises an important consideration, as the magnitude of the ZP effect may differ, for instance, in a 1+SQ design. On one hand, the ZP effect might appear more pronounced because the contrast between the alternatives is stronger than in the 2+SQ design. On the other hand, this simpler choice context might also increase the prominence of the SQ effect itself. It is therefore an empirical question how these competing effects would resolve, something that would require a new data collection effort. As the 2+SQ format is itself a common and widely applied design, understanding the ZP effect within this specific context remains a critical and relevant research objective.

In SP1, ZP and SQ effects are perfectly confounded. In the second treatment (SP2), both free and non-free SQ alternatives are allowed for separation of the ZP effects from the SQ effects. This setting could be relevant in cases where the SQ may be associated with a necessary out-of-pocket cost (e.g., a tax increase to maintain an otherwise deteriorating environmental state). In SP2, respondents were informed that a small service fee (1-3 zł) might be introduced to maintain the current Wi-Fi infrastructure. This framing was intended to reflect how "free" public services often involve hidden costs, a parallel to many environmental SC analysis where do-nothing scenarios entail small taxes or levies (e.g., Ahtiainen et al., 2023). In SP3, the SQ alternatives are dropped altogether to focus on the trade-offs between alternatives where zero or near-zero costs are included. This could be formulated as a 'forced choice' where certain public investments need to be made to reach specific policy targets (e.g. following the water framework directive, the nature restoration law, or decarbonisation targets). Small cost levels are incorporated in SP3 to separate non-linear cost sensitivity and ZP effects.

It is noted that the inclusion of a SQ alternative in SC survey can have profound implications for model outcomes and welfare estimates. Recent studies emphasize that SQ effects can result from task framing rather than actual preferences, particularly when the SQ is framed as a zero-cost option (Oehlmann et al., 2017). In water policy contexts, Lanz and Provins (2015) found that SQ choices do not necessarily reflect underlying preferences and can lead to biased regulatory guidance if not properly accounted for.

Beyond SQ framing, the format of the choice set – forced vs. unforced – has also been shown to affect respondents' trade-off behaviour. Veldwijk et al. (2014), using a health SC analysis, found that including an opt-out option significantly altered WTP estimates, suggesting that choice format and SQ inclusion jointly influence welfare measures.

More recently, Zachariou et al. (2025) showed that eliciting respondents' perceived SQ prior to choice tasks can reduce SQ bias and increase engagement, offering a practical strategy to mitigate design-induced distortions. Similarly, Boxebeld (2024) provide a systematic review highlighting how task sequencing and number of alternatives influence error variance, scale heterogeneity, and SQ selection rates. In our design, SP2 adopts a conventional 3-alternative unforced choice format with a SQ option, while SP3 implements a simplified 2-alternative forced choice design without an SQ. Following this literature, we interpret SP3 as a lower-complexity design useful for isolating the zero-price effect, not as a direct analogue to SP2. Differences in the number of alternatives and complexity are accounted for through joint modelling with scale parameters (see Section 4.4).

The sequential presentation of the three treatments may introduce order effects, potentially confounding observed preferences (Day et al., 2012; Carson & Groves, 2007). Such effects could include position-dependent fatigue effect, where respondents become increasingly inclined towards options with lower costs (e.g. SQ/ZP option) or higher attribute levels (e.g. data limit) as they progress through the tasks. This is of particular concern as any fatigue following SP1 could confound the intended identification of SQ and ZP effects in SP2. Another possibility is that respondents may develop a stronger tendency to reject costly 4G plans in favour of SQ over time, which could again influence the estimated ZP and SQ effects. We therefore include model specifications and diagnostic tests in later sections of the paper to assess the likelihood of such order effects influencing our results.

Respondents answer 26 choice tasks in total. In SP1 and SP2 respondents make 8 choice sets each, and 10 choices are recorded in SP3. The split into three SP experiments introduces natural breaks between task sets, which helps mitigate fatigue effects that could otherwise arise from presenting all 26 tasks as a single block. All 3 SP experiments are created using Bayesian *D*-efficient designs, with SP1 and SP2 each comprising 2 blocks of 8 choices and SP3 comprising 3 blocks of 10 choices, resulting in a total of 62 unique choice tasks in the sample. The normally distributed priors for the coefficients of interest are obtained from pilot surveys. **Table 1** provides an overview of the attributes and levels set out for each treatment.

Table 1. Overview of attributes

Treatment	Alt	Monthly fee (zł)		4G data limit (GB/month)	4G data accessibility (# of devices)
		Wi-Fi (campus)	4G LTE data		
SP1	SQ	0	-	-	-
	Alt 2/3	0	5 / 10 / 15 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3
SP2	SQ	0 / 1 / 3	-	-	-
	Alt 2/3	0 / 1 / 3	5 / 10 / 15 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3
SP3[1]	Alt 2/3	-	0 / 1 / 2 / 3 / 5 / 8 / 10 / 20 / 30 / 40	3 / 5 / 10 / 20	1 / 3

[1] Although there are only two choices presented in SP3, we retain the numbering of the two non-free alternatives for the 4G data package in SP1 and SP2 for consistency in summary of model results. Namely, 'alternative 2' refers to the first 4G data package and 'alternative 3' refers to the second 4G data alternative.

2.2. Individual treatment

2.2.1. SP1 – Zero cost SQ alternatives

The SQ alternative presented in SP1 is assumed to be free of charge. When selecting the SQ students can rely on the free Wi-Fi connection already provided by the university. The alternative 4G LTE broadband packages offer students the use of high-speed data transfer both within and outside the university. The browsing speed offered by the free Wi-Fi service is known to students to be slower compared to the 4G LTE data connection. The broadband packages vary in terms of the 4G data limit (gigabytes per month), the number of devices they can use to connect, and monthly costs (zloty per month, where 1 zloty equates to roughly €0.23). Students are informed that the university will offer all students both a SIM card and a USB modem (the size of a dongle/pendrive) with Wi-Fi connectivity free of charge.

2.2.2. SP2 – Zero and non-zero cost SQ alternatives

SP2 intends to isolate the ZP effect from the overall preference for remaining in the SQ. To achieve this a small charge of either 1 Polish Zloty (zł) or 3zł is added to the standard Wi-Fi access (i.e. the SQ option). These small costs are described as a requirement to maintain current service levels. In terms of the experimental design, non-zero cost levels are presented in 10 out of the 16 unique choice tasks in SP2. The remaining 6 choice tasks offer a free SQ alternatives, which are distributed equivalently across the two blocks of the design. In SP2, choosing any of the 4G LTE data packages involves paying both the minimal charges for the campus-wide Wi-Fi connectivity and the additional costs of the 4G LTE data package. This implies that the minimal price gap between the 4G LTE data package and the SQ alternatives remains at 5zł, which is the same as in the SP1 (see also **Table 1**).

2.2.3. SP3 – No SQ alternative

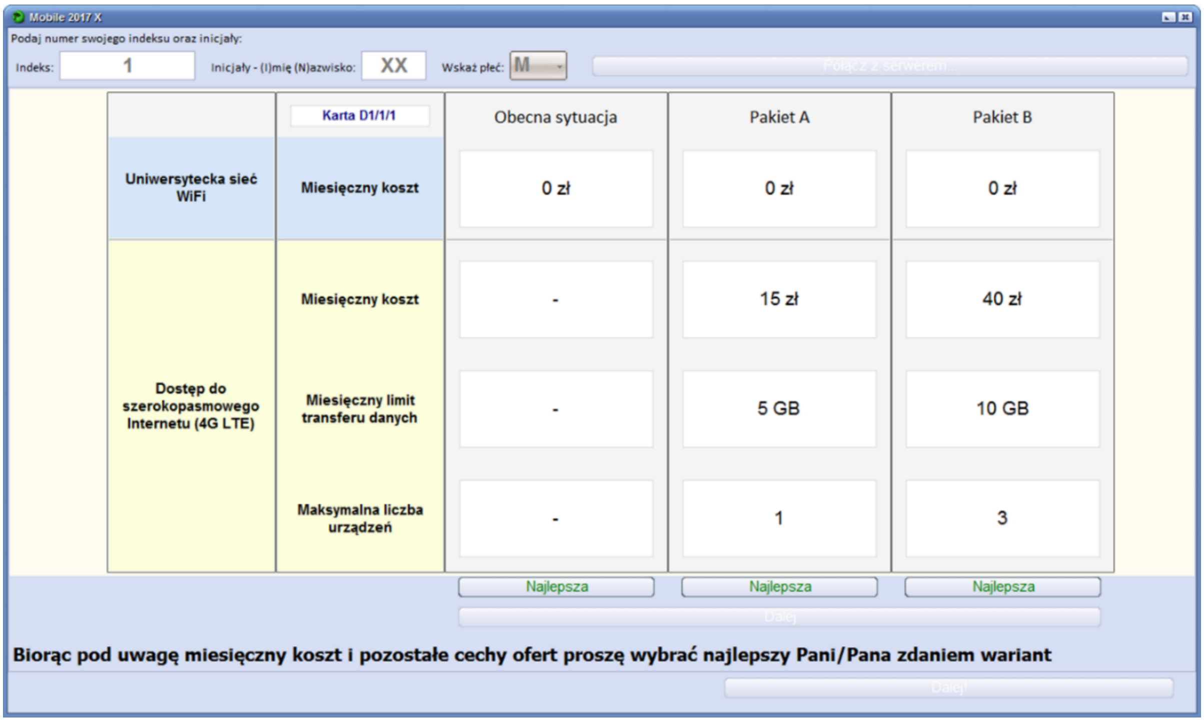
SP3 presents binary choices between two 4G LTE data packages. The removal of the SQ alternative is designed to ensure that no status quo effect comes into play at all. Respondents are asked to choose between a free and non-free alternative in 3 out of 10 choice tasks and to choose between two non-free 4G LTE data packages in the remaining 7 choice tasks. Small cost levels (1 zł, 2 zł and 3 zł) are present in this treatment to capture the cost sensitivity around near-zero cost levels such that we can additionally distinguish the ZP effect from non-linearity in cost sensitivity.

2.2.4. Data collection

The SC experiment is carried out through a survey app (see **Figure 1**). The presence of the SQ option in SP1 and SP2 creates scope for non-trading, and a follow-up question was used to understand the reasons when this occurs. The rates of SQ non-trading are 11% and 9% in SP1 and SP2, respectively. Since most (37 out of 41) of the non-traders indicated that they were satisfied with the existing service levels (either Wi-Fi or their own 4G subscriptions), all non-traders are therefore retained in the analysis. We have also tested the cases in SP2 (SP2-L1 and SP2-BC1 summarised in a later section) by excluding the remaining four non-traders that could be considered indicative of protest behaviour against charging of Wi-Fi services, and we found the resulting parameter signs, sizes, and WTP estimates remained comparable, indicating that the overall findings are robust to their inclusion.

A pilot survey covering 106 students was carried out prior to the main survey. Model results based on the pilot survey data were reasonable and the parameter estimates were of the right sign. The parameter estimates from the pilot survey were then used to update the priors in the experimental design. The main survey which took place in in December 2017 collected responses from 302 students in total.

Figure 1. Sample SP1 choice task in the SC survey app



3. Methodology

3.1. Model specification

The data collected are analysed using the standard Random Utility Maximisation (RUM)-based choice model, where the indirect utility $\mathrm{U_{jnt}}$ obtained for an individual n (with $\mathrm{n} = 1, \ldots, \mathrm{N}$) for alternative j (with $\mathrm{j} = 1, \ldots, \mathrm{J}$) in choice task t is decomposed into a deterministic component $\mathrm{V_{jnt}}$ and a random component ϵ_{jnt}:

$$\mathrm{U_{jnt}} = \mathrm{V_{jnt}} + \epsilon_{\mathrm{jnt}} \tag{1}$$

It is assumed that ϵ_{jnt} follows an extreme value distribution across alternatives. Assuming linear attribute sensitivities for the base specification, the deterministic component of the utility of alternative j applied for all three treatments can be written as:

$$\mathrm{V_{jnt}} = \delta_{\mathrm{j}} + \delta_{\mathrm{ZP}}\left(\mathrm{Cost_{jnt}} == 0\right) + \beta_{\mathrm{cost}}\mathrm{Cost_{jnt}} \quad + \beta_{\mathrm{dlim}}\mathrm{Dlim_{jnt}} + \delta_{\mathrm{dev_j}}(\mathrm{Dev_{jnt}} == 3) \tag{2}$$

where δ_{j} is a constant associated with alternative j to capture the average effect on utility due to the tendency of choosing a particular alternative. This is normalised to zero for alternative 3. As the SQ alternative is the left-most alternative (i.e. $\mathrm{j} = 1$), δ_1 captures the SQ effects in SP1 and SP2. In addition, δ_{ZP} is a dummy variable estimated in the case where the alternative j is a zero-price alternative. δ_{ZP} is only identified in SP2 and SP3, because in SP1 δ_{ZP} is perfectly confounded with δ_1 since the SQ is always free of charge in this experimental design. β_{cost} is the marginal utility associated with the total cost for alternative j, $\mathrm{Cost_{jnt}}$, which includes the costs for both the 4G LTE data package and the Wi-Fi, expressed in Polish złoty (zł)[2]; β_{dlim} is the marginal utility associated with the data limit of the 4G LTE data package, $\mathrm{Dlim_{jnt}}$, expressed in gigabytes (GB) per month; $\delta_{\mathrm{dev_j}}$ is a dummy variable estimated when the alternative j allows up to 3 devices to access the 4G LTE mobile data ($\mathrm{Dev_{jnt}} = 3$). As discussed in the next subsection, some model specifications allow departures from the base linear-in-attribute specification to include the possibility of non-linear sensitivities to the data limit and/or the cost attribute.

[2] Since the cost items are presented to respondents separately, we also take into consideration that respondents may respond to the costs of Wi-Fi and 4G LTE data packages differently (i.e. different cost sensitivities). However, test results indicated that the use of a generic cost sensitivity was appropriate. In an initial linear-in-cost model using SP2 data, we specified separate cost components for Wi-Fi and 4G LTE data. A likelihood ratio test did not reject the simpler specification using total cost (p = 0.275), supporting the use of a combined cost term.

3.2. Modelling non-linearity

A Box-Cox transformation (Box and Cox 1964) is adopted to incorporate the possibility of non-linearity in the marginal utility for the continuous attributes of cost and data limits. The Box-Cox transformation applies a flexible functional form that estimates the degree of non-linearity present in the data and is commonly applied in the transportation literature (Daly 2010; Gaudry, Jara-Diaz, and Ortuzar 1989; Rich and Mabit 2016). The transformation of the presented total cost for a given alternative is given by:

$$\mathrm{Cost}_{\mathrm{jnt}} = \begin{cases} \frac{\mathrm{Cost}_{\mathrm{jnt}}^{\lambda}-1}{\lambda}, \ \lambda \neq 0;\ \mathrm{Cost} > 0 \\ \ln\,(\mathrm{Cost}_{\mathrm{jnt}}),\ \lambda = 0;\ \mathrm{Cost} > 0 \end{cases} \tag{3}$$

where $\lambda = 1$ implies a linear effect while a logarithmic transformation is obtained as λ approaches 0.

Based on earlier model results respondents show decreasing sensitivity to the data limit of the 4G LTE data package. As the corresponding Box-Cox parameter approached zero (λ =0.059; t =0.47 in SP3 data), we apply the log-transformation to the data limit attribute, $\ln\,(\mathrm{Dlim}_{\mathrm{jnt}})$, across all model specifications.

Willingness-to-pay measures are calculated for the data limit, which represents the marginal rate of substitution between 4G LTE data limit and cost. This is given by the ratio of the partial derivative of the indirect utility function with respect to data limit to the partial derivative with respect to cost. Since a log-transformation of the data limit attribute is applied to all model specifications, the partial derivative with respect to data limit becomes $\beta_{\mathrm{dlim}}/\mathrm{Dlim}$. The partial derivative with respect to cost, however, varies depending on the estimated Box-Cox parameter. When cost sensitivity is specified linearly, then the WTP for data limit becomes $\frac{\beta_{\mathrm{dlim}}}{\mathrm{Dlim}}/\beta_{\mathrm{cost}}$. When the possibility of non-linearity in cost sensitivity is incorporated in the utility formulation using a Box-Cox transformation, the WTP for data limit is given by:

$$\mathrm{WTP}_{\mathrm{dlim}} = \frac{\partial V/\partial \mathrm{Dlim}_{\mathrm{LN}}}{\partial V/\partial \mathrm{Cost}_{\mathrm{BC}}} = \frac{\beta_{\mathrm{dlim}}/\mathrm{Dlim}}{\beta_{\mathrm{cost}}(\mathrm{Cost})^{\lambda-1}} \tag{4}$$

where $\lambda \geq 0;\ \mathrm{Cost} > 0;\ \mathrm{Cost}_{\mathrm{BC}} \sim \mathrm{BoxCox}(\mathrm{Cost};\lambda)$

Equation 4 shows that the WTP calculation depends on selected monthly cost and data limit levels. A set of reference measures is thus needed for comparing WTP estimates across scenarios, as opposed to simply comparing to an average WTP at sample level in the case where marginal utilities are specified linearly. Two data limit levels at 5GB and 20GB and three cost levels at 3zł, 10zł, and 30zł are selected for summarising WTP estimates. This results for the six reference WTP measures are compared across all models in this paper. The Delta method is used to obtain the estimates of error in the derived WTP measures (Daly, Hess, and De Jong 2012). The computation of standard errors for each of the three cost specifications varying with λ are outlined in detail in **Appendix A**.

3.3. Compensating Variations

In addition to the marginal WTP measures, we are also interested in assessing how modelling the ZP effect and allowing for non-linearity in cost sensitivities affect would affect welfare estimates. To accommodate non-linear income effects (i.e., a non-constant marginal utility of income), we follow the simulation approach outlined in Herriges & Kling (1999), based on the simulation framework suggested by McFadden (1999) to estimate compensating variations (CV).

Our proposed policy increases the data limit by 10 GB for the two priced 4G LTE products (i.e., alternatives 2 and 3), leaving the status quo alternatives unchanged in SP2. CV is defined as the uniform price uplift (i.e., an income reduction) across all three alternatives after the improvement that returns expected utility to the same as pre-policy level. The procedures as follows:

1. Compute the deterministic component of utility, V_{jt}, for each alternative j in task t, from the estimated parameters and observed attributes (including ZP constant where applicable).
2. Generate one million random draws ($n = 1, \dots, 1000000$) from uniform density and transform to Gumbel distribution (Type 1 Extreme Value): $\epsilon_{jnt} = -\ln(-ln(u_{jnt}))$, where $u_{jnt} \sim Uniform(0,1)$.
3. Compute maximum expected utility for the reference case: $Max(U_{jnt}^{ref} = V_{jnt}^{ref} + \epsilon_{jnt})$.
4. Apply policy change of increasing 10GB to the data limits of alternatives 2 and 3, and calculate the new V_{jnt}^{new}, U_{jnt}^{new}, and $Max(U_{jnt}^{new})$, whilst holding the same error terms ϵ_{jnt}.
5. For each draw n and choice task t, obtain the CV_{nt} in which increase in price is expected across all three alternatives when quality goes up (i.e., +10GB of 4G LTE data limits), such that: $Max(V_{jnt}^{new}(cost_{jnt} + CV_{nt}) + \epsilon_{jnt}) = Max(V_{jnt}^{ref}(cost_{jnt}) + \epsilon_{jnt})$

6. Obtain expected CV by averaging CV_{nt} across all draws and 16 choice tasks in SP2.
7. Verify that the mean of the expected maximum utility estimated has negligible difference from the closed form logsum, such that: $\log \sum e^{V_{jnt}} + \gamma = \mathrm{E}\left(Max\left(U_{jnt}\right)\right)$, where γ is the Euler constant term.

4. Empirical results

4.1. SP1 – Zero cost SQ alternatives

We first estimate the basic linear-in-attributes utility specification, including two alternative specific constants (Model SP1-L1 in **Table 2**). All parameter estimates in Model SP1-L1 are statistically significant at 95% confidence level. The SQ constant, δ_{alt1}, is positive, and shows that respondents have a strong preference for remaining in the SQ. However, due to the perfect confounding between the ZP-effect and δ_{alt1} this interpretation needs to be treated with caution. In line with expectations, we observe positive coefficients for larger data limits and the ability to use more devices. We also tested the Box-Cox transformation of costs, but it only gives marginal improvements in final LL and hence this non-linear specification of cost sensitivity is rejected for Model SP1-L1 based on likelihood ratio test (p=0.221).

Marginal WTP for 4G LTE data derived from Model SP1-L1 only varies with the size of the imposed data limit in accordance with the non-linear functional form for this attribute. Results show that respondents are willing to pay 2.21zł for each additional GB of 4G LTE data for a package that comes with 5GB of data limit. A significantly lower marginal WTP for data limit is estimated at 0.55zł/GB when a higher data limit of 20GB is offered. This 75% decrease in marginal WTP is equivalent to the relative ratio in data limit (i.e., 5GB vs. 20GB), as the marginal WTP is inversely proportional to the size of the data limit. Robust *t*-ratios for the six reference marginal WTP values remain the same as both the standard error (see **Appendix A**) and the WTP (see **Section 0**) are inversely proportional to the data limit.

To test for potential order effects, we estimated a variant of the SP1 model incorporating an interaction between choice number and the SQ ASC. The likelihood ratio test comparing this with the base model failed to reject the simpler model (p = 0.145), suggesting that the SQ coefficient does not significantly vary across SP1 choices. This provides evidence that order effects are unlikely to be driving the observed SQ preferences.

Table 1. Estimation results for SP1 and SP2

		SP1 - L1 Linear Cost		SP2 - L1 Linear Cost		SP2 - BC1 Box-Cox~(Cost)		
Respondents		302		302		302		
Obs		2416		2416		2416		
Final LL		-2295.33		-2173.93		-2165.67		
AIC		4600.66		4359.85		4345.34		
Adj. ρ^2		0.133		0.179		0.181		
Parameter estimates		est.	rob. t-rat(0)	est.	rob. t-rat(0)	est.	rob. t-rat(0)	rob. t-rat(1)
ZP (δ_{ZP})		-	-	0.246	3.38	0.083	1.06	
SQ $_{\text{alt1}}$ (δ_{alt1})		0.737	4.84	0.531	3.03	-1.175	-1.59	
ASC$_{\text{alt2}}$ (δ_{alt2})		0.085	1.97	0.025	0.53	0.067	1.40	
Cost$_{\text{Linear}}$ (β_{cost})		-0.097	-16.74	-0.086	-20.36	-	-	
Cost$_{\text{Box-Cox}}$ (β_{cost})		-	-	-	-	-0.873	-2.05	
Lambda$_{\text{Box-Cox}}$ (λ)		-	-	-	-	0.261	1.63	-4.36
Data Limit$_{\text{log}}$ (β_{dlim})		1.074	16.82	0.904	15.22	1.038	14.10	
Multi-Access (δ_{mdev})		0.412	6.78	0.396	5.54	0.327	4.53	
WTP (zł/GB) at reference 4G LTE data limit & total cost								
Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)	est.	rob. t-rat(0)	est.	rob. t-rat(0)	
5	3	2.207	17.77	2.110	14.30	0.535	2.04	
5	10	2.207	17.77	2.110	14.30	1.304	2.16	
5	30	2.207	17.77	2.110	14.30	2.937	2.19	
20	3	0.552	17.77	0.528	14.30	0.134	2.04	
20	10	0.552	17.77	0.528	14.30	0.326	2.16	
20	30	0.552	17.77	0.528	14.30	0.734	2.19	

4.2. SP2 - Zero and non-zero cost SQ alternatives

4.2.1. Linear cost specification

SP2 is devised to disentangle the ZP-effect from δ_{alt1} effects by allowing both zero and non-zero costs for the SQ alternatives. Model SP2-L1, also presented in **Table 2**, follows the same specification as Model SP1-L1 but additionally includes the ZP dummy δ_{ZP}. Note that the model is estimated on a different dataset and hence, only the WTP estimates are directly comparable across the two models. All parameters are statistically significant at 95% confidence level, except for the constant associated with the middle alternative (i.e. δ_{alt2}). The estimates for δ_{ZP} and δ_{alt1} indicate that a significant share of what would otherwise entirely be classified as a preference for the SQ can now be attributed to the ZP effect. Nevertheless, the status quo continues to exhibit a positive level of attractiveness, even after controlling for all other explanatory variables.

Relative to Model SP1-L1, the marginal WTP estimates reduce slightly by 4.4% to 2.11zł/GB and 0.53zł/GB at respectively data allowances of 5GB and 20GB. The differences in WTP between the two treatments are not statistically significant (*t*-ratio of 0.50) indicating that the impacts of introducing a SQ option associated with a small payment have a limited impact whilst enabling us to isolate the ZP-effect.

As we did not observe significant variation in the SQ coefficient across SP1 choice tasks, we consider it unlikely that the shift in SQ preferences from SP1 to SP2 is driven by order effects.

4.2.2. Non-linear cost specification

Model SP2-BC1 presented in **Table 2** implements the Box-Cox transformation on the cost attribute. Accordingly, this specification ensures that potential biases in $\delta_{alt1}, \delta_{ZP}$ in Model SP2-L1 due to non-linear cost sensitivities are accounted for. A significant improvement in log-likelihood is observed relative to Model SP2-L1 (LR-test p-value < 0.01) by estimating the Box-Cox parameter λ. It's estimate is close to zero, implying strong non-linearity. As opposed to the findings from the Model SP2-L1, δ_{ZP} and δ_{alt1} constants are no longer statistically significant at the 95% confidence interval. This finding is in line with Hess et al. (2011) who highlight the risk of obtaining biased estimates for the alternative specific constants, and in our case the ZP dummy, when the utility function is incorrectly specified.

As a result of the non-linear cost sensitivity WTP estimates also give a rather different picture relative to Models SP1-L1 and SP2-L1. Marginal WTP estimates for increasing the data limit by 1 GB are smaller at small cost levels, but exceed earlier reported levels for more expensive alternatives suggesting a rapid decrease in cost sensitivity. When the costs for the 4G LTE package are set to 3zł, marginal WTP for increasing the data limit by 1 GB reduces by 75% to 0.54zł/GB (at 5GB) and 0.13zł/GB (at 20GB) in Model SP2-BC1 relative to Model SP2-LC1. This reflects the cost damping effect implied by the Box-Cox transformation, which gives higher cost sensitivity at small cost levels and lower cost sensitivity at higher levels. The marginal WTP for increasing the data limit by 1 GB when the 4G LTE package is offered at 30zł increases in Model SP2-BC1 to 2.94zł/GB and 0.73zł/GB respectively.

4.2.3. Compensating Variations

In addition to marginal WTP, we also examine how accounting for the ZP effect influences welfare under both linear and non-linear cost sensitivities, focusing on the SP2 dataset. As such, we estimate the linear and non-linear models without the ZP constant, labelled SP2-L1 (No ZP), and also SP2-BC1 (No ZP), respectively in **Table 2**. We focus on SP2 here because, unlike in SP1, its design allows the ZP effect to be separately identified from the status quo. A comparison against the corresponding specifications with ZP constants reported earlier in **Table 1**, excluding the ZP constant leads to only modest changes in the remaining coefficients. The likelihood-ratio tests indicate that in the linear case, dropping ZP constant significantly worsens model fit ($p = 0.01$), whereas in the non-linear case, excluding ZP constant does not ($p = 0.43$), which is consistent with the ZP effect being largely absorbed once non-linearity in price is modelled, as discussed above.

Table 2. Estimation results for SP2 without ZP constants

	SP2 - L1 (No ZP) Linear Cost		SP2 - BC1 (No ZP) Box-Cox~(Cost)		
Respondents	302		302		
Obs	2416		2416		
Final LL	-2177.23		-2165.98		
AIC	4364.46		4343.97		
Adj. ρ^2	0.1778		4378.710		
Parameter estimates	est.	rob. t-rat(0)	est.	rob. t-rat(0)	rob. t-rat(1)
ZP (δ_{ZP})	-	-	-	-	
SQ $_{\text{alt1}}$ (δ_{alt1})	0.640	3.82	-1.356	-1.74	
ASC$_{\text{alt2}}$ (δ_{alt2})	0.027	0.57	0.072	1.50	
Cost$_{\text{Linear}}$ (β_{cost})	-0.088	-20.06	-	-	
Cost$_{\text{Box-Cox}}$ (β_{cost})	-	-	-0.997	-2.18	
Lambda$_{\text{Box-Cox}}$ (λ)	-	-	0.220	1.46	-5.15
Data Limit$_{\text{log}}$ (β_{dlim})	0.926	15.46	1.055	14.72	
Multi-Access (δ_{mdev})	0.401	5.58	0.322	4.46	

We have estimate CV measures based on all the 4 model specifications to understand the changes in welfare due to policy change of 10 GB increase in 4G LTE data limits for the 2 priced alternatives (i.e., Alternatives 2 and 3), which are summarised in **Table 3**. Overall, the changes in welfare follow expected trend: when the SQ alternative (Alternative 1) is free, excluding modelling of the ZP effect understates its utility and market share, hence the additional data limits to the priced options (Alternatives 2 and 3) appears disproportionately valuable, hence overstating the CV.

In the linear models, the specification without ZP constants (SP2-L1 (NoZP)) overestimates average CV by +6% overall (from 5.77zł to 6.11zł), driven largely by the 6 choice tasks with a ZP SQ alternative (+27.8%, from 4.43zł to 5.66zł). For the remaining 10 non-ZP choice tasks, differences in average CV are much smaller (-0.9%), reflecting only minor shifts in parameter estimates. In the non-linear models, excluding ZP constant has a much smaller effect overall (-0.4%, from 4.12zł to 4.11zł), with the same direction pattern – higher average CV in the 6 choice tasks with ZP SQ alternatives (+3%, from 3.41zł to 3.51zł) offset by the lower average CV in the 10 non-ZP choice tasks (-1.6%, from 4.45 to 4.38). This aligns with the finding that the explicit ZP constant becomes far less significant once non-linearity in costs is modelled. Overall, excluding ZP can significantly change welfare estimates, especially in the linear cost formulation, whereas non-linearity in costs largely reduces this issue. We note that **Table 3** only presents CV comparisons within the SP2 dataset. The average CV from SP1 is not included, as it is based on a different set of choice tasks and is therefore not directly comparable.

Table 3. Compensating variation (CV, zł) for +10 GB increase in data limits in SP2

Cost sensitivity	Linear			Non-linear		
Model	SP2 - L1	SP2 - L1_NoZP		SP2 - BC1	SP2 - BC1_NoZP	
	Avg CV	Avg CV	vs. SP2-L1	Avg CV	Avg CV	vs. SP2 - BC1
6 tasks with ZP SQ alt	4.43	5.66	27.8%	3.41	3.51	3.0%
10 tasks without ZP alts	6.37	6.32	-0.9%	4.45	4.38	-1.6%
All 16 choice tasks	5.77	6.11	6.0%	4.12	4.11	-0.4%

4.3. SP3 – No SQ alternative

4.3.1. Linear cost specification

SP3 presents respondents with binary choices with the possibility of zero cost in one of the two 4G LTE packages available. Respondents are no longer presented with an SQ option. This setup avoids any confounding between ZP and SQ effects entirely. Moreover, small costs are presented to ensure that the ZP effect can be distinguished from the non-linearity in cost sensitivity near the zero price. This treatment represents the best ‘test-bed’ for capturing the ZP effect amongst the 3 treatments. Similar to the previous treatments, a basic linear-in-cost model with a dummy variable to capture any potential ZP effect is estimated (Model SP3-L1). All parameter estimates in **Table 3** are statistically significant at the 95% confidence level, and they are of the expected sign. The positive estimate for δ_{ZP} suggests the presence of a ZP effect in this model specification. The marginal WTP values for increasing the data limit are reduced by 22% relative to Model SP2-L1 to 1.64zł/GB and 0.41zł/GB at the respective data limits of 5GB and 20GB.

Table 4. Estimation results for SP3

		SP3-L1 Linear Cost		SP3-BC1 Box-Cox~(Cost)		
Respondents		302		302		
Obs		3020		3020		
Final LL		-1553.59		-1509.07		
AIC		3117.18		3030.14		
Adj. ρ^2		0.2554		0.2762		
Parameter estimates		est.	rob. t-rat(0)	est.	rob. t-rat(0)	rob. t-rat(1)
ZP (δ_{ZP})		0.501	5.78	0.362	3.84	
ASC_{alt2} (δ_{alt2})		0.108	2.60	0.073	1.73	
$\text{Cost}_{\text{Linear}}$ (β_{cost})		-0.121	-19.32	-	-	
$\text{Cost}_{\text{Box-Cox}}$ (β_{cost})		-	-	-0.535	-7.74	
$\text{Lambda}_{\text{Box-Cox}}$ (λ)		-	-	0.469	9.90	-11.22
$\text{Data Limit}_{\text{log}}$ (β_{dlim})		0.992	13.83	1.181	14.91	
Multi-Access (δ_{mdev})		0.299	5.53	0.334	6.04	
WTP (zł/GB) at reference data limit & cost						
Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)	est.	rob. t-rat(0)	
5	3	1.642	16.50	0.791	7.55	
5	10	1.642	16.50	1.500	7.87	
5	30	1.642	16.50	2.689	7.97	
20	3	0.410	16.50	0.198	7.55	
20	10	0.410	16.50	0.375	7.87	
20	30	0.410	16.50	0.672	7.97	

4.3.2. Non-linear cost specification

Again we observe a significant increase in model fit by applying a Box-Cox transformation to the cost attribute in Model SP3-BC1 relative to Model SP3-L1. The estimated Box-Cox parameter λ is, however, slightly higher than in Model SP2-BC1 implying a lower degree of cost damping in this binary choice context. All parameters in Model SP3-BC1 are statistically significant at 95% confidence level except for δ_{alt2}. The size and significance of the ZP dummy, δ_{ZP}, reduces once the cost sensitivity takes on a non-linear form. This implies that the ZP effect, albeit still being picked up when cost sensitivity is specified non-linearity, has been over-stated using a linear-in-cost specification in model SP3-L1. This is consistent with our findings for Model SP2-BC1.

The comparison of the WTP for increasing the data limit for the 4G LTE packages across linear and non-linear cost models in SP3 gives a very similar picture as in SP2. WTP values estimated at 3zł and 10zł are significantly lower when cost sensitivity is specified nonlinearly, and vice versa when the 4G LTE package is priced higher at 30zł. In contrast to the model assuming linear cost sensitivity, differences in WTP computed based on non-linear cost function between SP2 and SP3 are not statistically different across all cost levels, as presented in **Table 5**. The insignificant difference in WTP estimates between SC designs respectively including and excluding a SQ alternative is reassuring, as it lends support to the consistency of trade-off behaviour regardless of the presence of a SQ option. The removal of the status quo alternative in SP3 was, again, intended to eliminate potential confounding between SQ and ZP effects, thereby allowing for a cleaner assessment of the underlying ZP effect.

Table 5. WTP differences between SP2 and SP3

Reference cost and data limit		Linear-in-cost model SP3-L1 vs SP2-L1				Non-linear-in-cost model SP3-BC1 vs SP2-BC1			
Data Limit (GB)	Cost (zł)	SP3 est.	SP2 est.	diff.	rob. *t*-rat (diff)	SP3 est.	SP2 est.	diff.	rob. *t*-rat (diff)
5	3	1.64	2.11	-22%	*2.63*	0.79	0.54	48%	*0.90*
5	10	1.64	2.11	-22%	*2.63*	1.50	1.30	15%	*0.31*
5	30	1.64	2.11	-22%	*2.63*	2.69	2.94	-8%	*0.18*
20	3	0.41	0.53	-22%	*2.63*	0.20	0.13	48%	*0.90*
20	10	0.41	0.53	-22%	*2.63*	0.37	0.33	15%	*0.31*
20	30	0.41	0.53	-22%	*2.63*	0.67	0.73	-8%	*0.18*

4.4. Joint modelling

Given the similar findings across the different experimental designs, i.e. presence of a ZP effect and non-linear cost sensitivity, we continue by presenting a joint modelling specification combining the data from all three SP experimental designs. The results for Model Joint-BC1 are presented in **Table 5**. In addition to the parameters estimated before, the model now also includes relative scale parameters across the three experimental designs (μ_{SP1}, μ_{SP2} and μ_{SP3} respectively). The scale parameter for SP3 is normalised to one.

Most interestingly we now find a negative preference to stay at the SQ, implying that people prefer having access to 4G LTE data services as opposed to the standard university WiFi provisions. However, the presence of the positive ZP-effect means that people are perhaps overly attracted to the free ZP-effect, especially in SP1 where the SQ is the only free alternative. Consistent with earlier models we observe a non-linear cost sensitivity highlighting that marginal WTP estimates will increase as base cost levels for 4G LTE packages increase, and we observe a positive preference and WTP for increasing data limits and the number of devices one can make use of. The relative scale parameters for SP1 and SP2 are estimated to be lower than one. Since scale parameter is inversely proportional to the variance of the error term, smaller scale this suggests less deterministic behaviour (from the analyst's perspective) relative to SP3. This is not surprising as respondents are required to handle more alternatives in SP1 and SP2. This is in line with the argument that higher level of task complexity can lead to larger variance in random error term (Swait and Adamowicz 2001).

The WTP computed for the joint model largely fall between the values obtained for the non-linear in cost models in SP2 and SP3 and are hence consistent with the previous findings. As discussed before, the non-linear in cost model allows higher cost sensitivity for small cost levels and vice versa for higher costs. This leads to WTP which is 58% lower at small cost level (0.81 vs. 1.93 at 3zł and 5GB; 0.20 vs 0.48 at 20GB) and 45% higher for higher cost level (2.67 vs. 1.93 at 30zł and 5GB; 0.67 vs 0.48 at 20GB) when compared to the linear-in-cost specification.

Table 6. Joint estimation results

	Joint - BC1 Box-Cox~(Cost)		
Respondents	302		
Obs	7852		
Final LL	-5982.68		
SP1	-2303.29		
SP2	-2168.63		
SP3	-1510.77		
AIC	11985.36		
Adj. ρ^2	0.190		
Parameter estimates	est.	rob. t-rat(0)	rob. t-rat(1)
ZP (δ_{ZP})	0.313	4.37	
$SQ_{alt1, SP2}$ ($\delta_{alt1, SP1/2}$)	-0.391	-2.27	
$ASC_{alt2, SP1/2/3}$ (δ_{alt2})	0.064	1.66	
$Cost_{Box\text{-}Cox}$ (β_{cost})	-0.554	-7.58	

Lambda$_{Box\text{-}Cox}$ (λ)	0.458	9.62	-11.38
Data Limit$_{log}$ (β_{dlim})	1.228	16.95	
Multi-Access (δ_{mdev})	0.387	8.05	
Scale$_{SP1}$ (μ_{SP1})	0.852	16.16	-2.80
Scale$_{SP2}$ (μ_{SP2})	0.830	17.59	-3.61
Scale$_{SP3}$ (μ_{SP3})	1.000	-	

WTP (zł/GB) at reference data limit & cost

Data Limit (GB)	Cost (zł)	est.	rob. t-rat(0)
5	3	0.805	7.36
5	10	1.547	7.68
5	30	2.807	7.78
20	3	0.201	7.36
20	10	0.387	7.68
20	30	0.702	7.78

5. Conclusions

This paper builds on two recent papers focusing on the specification of the cost vector in stated choice surveys. Glenk et al. (2019) adopt a split-sample approach and show that the use of alternative cost vectors including a wide or small range of cost levels may influence emerging WTP estimates because of behavioural phenomena such as anchoring effects and attribute non-attendance, but also interactions with personal income. Ahtiainen et al. (2023) also adopt a split-sample approach and show the tendency to adopt the status quo increases when higher cost vectors are included. Notably they also deviate from standard practice and associate the status quo with a non-zero cost.

In this paper, we focus on two effects. First, we develop an experimental design setup enabling the identification of a zero-price effect which may explain the over attraction of the status quo in many stated choice surveys (e.g. Shampanier, Mazar, and Ariely 2007). The inability to separate the zero-price effect from the preference for the status quo due to perfect confounding in standard experimental designs may undesirably bias welfare estimates for policy changes that depart from the status quo. Note that this requires interpreting the zero-price effect as an undesirable behavioural effect in stated choice surveys we may wish to filter out. Separation of the zero-price effect from the pure preference from the status quo requires introducing variation in the cost associated with the status quo as in Ahtiainen et al. (2023). Note that our approach makes use of a within-sample approach and varies the costs of the status quo, including free options, across a range of choice tasks. The introduced costs associated with the status quo in our study are small. In practice, this could be implemented by reporting estimates of the actual operating costs of the status quo, and these may turn out to be larger. In those cases, the zero-price effect may be induced by changing the framing to 'no additional costs' and relative changes to this level. When adopting a standard linear-in-cost utility specification we find evidence of a strong zero-price effect under students for improving their access to fast and reliable 4G LTE broadband packages relative to the free on-campus WiFi offered.

The second effect explored in this paper relates to the specification of the cost attribute in the utility function. We introduce non-linearity in the utility function with respect to costs using the standard Box-Cox transformation and find evidence of cost damping effects. That is, the marginal utility of cost is decreasing as cost levels increase. A direct consequence of this non-linearity is that marginal WTP estimates, in our case for increasing the data limit by 1GB, increases when the cost level at which the marginal WTP is estimated increases. This finding is consistent with Glenk et al. (2019) and Ahtiainen et al. (2023) who identify that WTP estimates increase when higher cost levels are introduced. Most notably, when introducing non-linearity in the cost coefficient the identified preference for staying at the status quo may even change signs and the zero-price effect may decrease in order of magnitude. Moreover, marginal WTP estimates significantly differ from those obtained from the linear-in-cost models and are typically lower except for the high end of the cost range. Misspecification of the utility function may therefore result in bias in the estimated preference parameters associated with the status quo and the included attributes. Irrespective of the chosen utility specification for cost, we do find evidence of the presence of a zero-price effect.

Our recommendations based on the obtained results are to vary the cost associated with the status quo alternative, preferably across the choice tasks presented to the same individual. In many empirical applications associating small cost levels can be justified. Even a '*do nothing scenario*' carried forward into the future is typically associated with minor costs which need funding. Additionally, we recommend the use of many cost levels, including a couple of small cost levels to better identify the non-linear sensitivity with respect to cost. The inclusion of small cost levels for the proposed policy improvements are essential to remove any remaining bias in the preference for the status quo as much as possible. Again, we prefer doing so using a within-sample approach as opposed to the use of different cost vectors across subsamples (i.e. a split sample approach). Commonly applied blocking strategies in experimental design generation software will ensure a balanced distribution of presented cost levels, including zero and non-zero price levels for the status quo, across the sample such that non-linear sensitivities with respect to cost, the zero-price effect, and the preference for the status quo can be appropriately identified without (or at least lowering the change of) inducing sample specific behavioural traits as identified by Glenk et al. (2019) and Ahtiainen et al. (2023).

Where Hanley et al. (2001) explicitly argue for the inclusion of a status quo option for rooting the obtained estimation results in welfare economics, we also provide evidence that marginal WTP estimates for policy attributes can be obtained without the inclusion of a status quo. That is, we provide students with a forced choice between two 4G LTE broadband packages and obtain WTP estimates which are comparable and not significantly different from those obtained from the SP design including the option of selecting the standard WiFi option offered by the university. These results are consistent with the findings of Boyle and Özdemir (2009) regarding the inclusion/exclusion of the status quo option in the design. With many studies aiming to estimate marginal WTP estimates for the selected policy attributes without implementing the estimated utility function, including the alternative specific constants, for policy analysis leaving out the status quo option may be a desirable feature without inducing known issues associated with the inclusion of the status quo. This approach is common in SC surveys in transportation where route and mode choices do seldomly include the current route or mode choice. Of course, our recommendations and inference are based on a relatively small scale stated choice survey in a specific context. Accordingly, we would recommend further empirical validation in other domains, including environmental and health economics.

While zero-priced SQ alternatives may bias respondents toward the current state and thus lower WTP estimates, we acknowledge that a broader concern in environmental valuation is that WTP values can appear overly large. Our analysis shows that both biases can be mitigated by addressing the ZP effect directly and by incorporating non-linear cost sensitivity in model specifications. This contributes to improved reliability and policy credibility of SC-based welfare estimates. This emphasis on non-linearity is particularly important to avoid model misspecification, especially given prevailing practice in which the SQ constant is typically excluded from welfare calculations, even though, in principle, it forms part of the indirect utility function and should therefore be included (Boxall, Adamowicz and Moon, 2009).

Some of the recommendations provided by our analysis go against theoretical recommendations regarding the need to include the status quo alternative in the choice set (Hanley, Mourato, and Wright 2001), and the need to make use of a linear-in-cost utility function (Batley and Dekker 2019) to obtain valid welfare estimates. Our analysis describes a conventional trade-off between accounting for behavioural effects in the estimation of choice models, including the zero-price effect and non-linear cost sensitivities. Our recommendations for experimental design allow identifying such effects such that differences in emerging welfare estimates can be contrasted. Ultimately, the researcher will need to make a judgement call to either impose economic rationality on behavioural responses and adopt, hopefully only slightly, biased welfare estimates; or to account for various behavioural traits and develop ways filtering out these behavioural traits from welfare analysis (e.g. by ignoring the ZP effect dummy), or to develop ways in which these results rooted in behavioural economics can be used to provide policy recommendations, especially additional research is needed providing recommendations on how to aggregate welfare effects of different sizes across the population of interest. This remains a fruitful area of future research (e.g. Morey 2023).

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Appendix A

Following the notation as in Daly et al. (2012), we define Φ as a differentiable and invertible function of a number of model parameters β. Applying the Delta method, the variance of the function Φ is equal to:

$$var(\Phi) = \sum_{l=1}^{L} \phi_l'^2 \omega_{ll} + 2\sum_{l=2}^{L}\sum_{m=1}^{l-1} \phi_l' \phi_m' \omega_{lm}$$

CASE 1 ($\lambda > 0$): When data limit is log-transformed and cost is Box-Cox transformed, function Φ becomes:

$$\Phi = \frac{\partial V/\partial Dlim_{LN}}{\partial V/\partial Cost_{BC}} = \frac{\beta_{dlim}}{Dlim\,\beta_{cost}(Cost)^{\lambda-1}}$$

Individual elements Φ', which is the first derivative matrix of Φ, and the variance of Φ are given by:

$$\phi_k' = \frac{\partial \Phi}{\partial \beta^*}$$

$$For\ \beta^* = \beta_{dlim}: \qquad \phi_1' = \frac{1}{Dlim\,\beta_{cost}(Cost)^{\lambda-1}}$$

$$For\ \beta^* = \beta_{cost}: \qquad \phi_2' = -\frac{\beta_{dlim}}{Dlim\,\beta_{cost}^2(Cost)^{\lambda-1}}$$

$$For\ \beta^* = \lambda: \qquad \phi_3' = -\frac{\beta_{dlim}(\lambda-1)}{Dlim\,\beta_{cost}Cost^{\lambda}}$$

$$var(\Phi) = \phi_1'^2\omega_{11} + \phi_2'^2\omega_{22} + \phi_3'^2\omega_{33} + 2(\phi_2'\phi_1'\omega_{21} + \phi_3'\phi_1'\omega_{31} + \phi_3'\phi_2'\omega_{32})$$

CASE 2 ($\lambda = 0$): When data limit is log-transformed and cost is log-transformed, then Φ, Φ_k', and $var(\Phi)$ are given by:

$$\Phi = \frac{\partial V/\partial Dlim_{LN}}{\partial V/\partial Cost_{LN}} = \frac{\beta_{dlim}Cost}{\beta_{cost}Dlim}$$

$$For\ \beta^* = \beta_{dlim}: \qquad \phi_1' = \frac{Cost}{\beta_{cost}Dlim}$$

$$For\ \beta^* = \beta_{cost}: \qquad \phi_2' = -\frac{\beta_{dlim}Cost}{\beta_{cost}^2 Dlim}$$

$$var(\Phi) = \phi_1'^2\omega_{11} + \phi_2'^2\omega_{22} + 2\phi_2'\phi_1'\omega_{21}$$

CASE 3: When data limit is log-transformed, while cost is linear, Φ, Φ_k', and $var(\Phi)$ become:

$$\Phi = \frac{\partial V/\partial Dlim_{LN}}{\partial V/\partial Cost_{linear}} = \frac{\beta_{dlim}}{\beta_{cost}Dlim}$$

$$For\ \beta^* = \beta_{dlim}: \qquad \phi_1' = \frac{1}{\beta_{cost}Dlim}$$

$$For\ \beta^* = \beta_{cost}: \qquad \phi_2' = -\frac{\beta_{dlim}}{\beta_{cost}^2 Dlim}$$

$$var(\Phi) = \phi_1'^2\omega_{11} + \phi_2'^2\omega_{22} + 2\phi_2'\phi_1'\omega_{21}$$

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