# An empirical examination of reducing status quo bias in heterogeneous populations: evidence from the South African water sector

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# An empirical examination of reducing status quo bias in heterogeneous populations: evidence from the South African water sector

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## ABSTRACT

Choice experiments typically include a status quo option, which often describes the current scenario. This is to secure the validity and applicability of choice experiments. People have a propensity to choose what they are familiar with, despite being presented with alternatives that seem better (i.e. the 'status quo effect'). Various experiments have reliably demonstrated this effect. The tendency to prefer the current scenario disproportionally does not mimic real-life preferences; therefore, status quo bias is undesirable. In a split sample framework, we test for the effects of reducing status quo bias by considering a heterogeneous sample. We use generalised mixed logit models to carry out the tests. The tests reveal that presenting each split sample with a partially relevant status quo significantly reduces the status quo bias problem.

**Keywords:** choice experiments, heterogeneous, generalised mixed logit, status quo bias.

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## 1. Introduction

Choice experiments typically include a 'status quo' (SQ) option that describes the current situation. Respondents who participate in a choice experiment (CE) are generally asked to choose several times between hypothetical options and an SQ option. Thus, the SQ option is an 'opt-out' option to the offered alternatives in the choice sets. To secure the validity and applicability of CE studies, the SQ option should mimic real-life status quo choices. The SQ option essentially avoids the undesired effects linked to forced choices or ascertains whether respondents are satisfied with current packages. In certain circumstances, when respondents choose the SQ option it signifies their level of satisfaction with the current packages (Lanz and Provins, 2015).

However, a large body of literature argues that the SQ option leads to the problem of SQ bias. This issue was first identified by Samuelson and Zeckhauser (1988), who described it as the respondents' disproportionate tendency to choose a default option. In the literature, it is often argued that respondents usually choose the SQ option to the extent that no real trade-offs are made between the given attributes. If this happens, there is a risk of biased empirical results, which may lead to incorrect practical inferences. SQ bias has been argued to emerge from issues such as task complexity, and the reality that respondents normally prefer the SQ they are currently experiencing, compared to designed options whose utility is hypothetical (Meyerhoff and Liebe, 2009; Scarpa et al., 2007). The existence of such factors makes SQ bias inevitable in CE surveys.

An SQ bias problem is undesirable because it leads to an underestimation of the welfare changes of a proposed policy change. In addition, as the SQ alternative is preferred too frequently, information is reduced regarding the relative values of different types of attributes associated with a policy change. This consequently reduces the effectiveness of stated preference surveys to elicit and identify preferences (Bonnichsen and Ladenburg, 2015). The status quo bias can have serious effects on empirical results as well as on policy choices.

Several attempts have been made in the literature to address SQ bias and the effects of imposing SQs on a heterogeneous sample. A significant number of CE studies impose hypothetical baselines as SQs. Some completely exclude the SQ option in the choice sets, while others replace it with a 'none' choice as an alternative opt-out option. Although excluding the SQ option may be a solution, in some instances including the SQ option is essential, because SQ choices may reflect genuine preferences for current packages (see Lanz and Provins, 2015). Another possible solution involves the use of individual-specific SQ options; in such cases, the SQ option is left blank, and respondents determine their own perceived SQs (Campbell et al., 2008; Hess and Rose, 2009).

Status quo bias studies tend to assume that treatment choice is on homogenous populations. Most of the studies test for bias without considering whether there might be a heterogeneous population. The implication of a heterogeneous population may be that the alternative representing the status quo situation does not resonate with some subpopulations. To address this, some studies divide the population into subgroups, and then present different status quos accordingly. In developing countries with high levels of inequality, such as South Africa and Brazil, the optimal treatment rule may be to divide the population into subpopulations, each of whose members share the same current situation; and then to conduct an experiment in which each subpopulation faces a status quo alternative with which they are familiar. This is an optimal method to secure the validity and applicability of the experiments. However, empirical studies show that when presented with alternatives that seem superior, CE participants tend to prefer what they already have. Considering that splitting the sample initially is meant primarily to ensure that each sub-sample is presented with an SQ that they already know, it is plausible that this trend would remain even in a case in which the population is divided, meaning that the status quo bias problem will persist. In this study, therefore, we are interested in assessing whether presenting a partially relevant SQ could reduce the SQ bias problem.

Our paper tests for the effects of introducing a partially relevant status quo aimed at reducing SQ bias in a CE eliciting households' preference for water service packages. We test these effects by comparing the utility functions and marginal willingness to pay estimates of two subpopulations (i.e. suburbs and townships). Each subpopulation is presented with two experiments: one containing a relevant SQ[3], and another containing a partially relevant SQ. The focus of the paper is on testing whether participants' likelihood of choosing the SQ is driven by the relevance or partial relevance of the SQ option. We hypothesise that the introduction of a partially relevant SQ reduces SQ bias. We make use of data from experiments on households' satisfaction with their municipal water service packages in Durban, a city in South Africa.

[3] A 'relevant status quo' in this study implies an SQ option that captures the current scenario for most participants in each subsample. It shows the water service package currently received by most participants in each subpopulation.

To the best of our knowledge, this is the first paper to test for the effects of reducing status quo bias by dividing population (based on economic segmentation) into two subpopulations (i.e. wealth and poverty) and presenting each subpopulation with two different choice experiments. In the first treatment, respondents in each subpopulation are presented with a series of choice sets, each with a status quo choice that resonates with them (i.e. it is relevant). In another treatment, each subpopulation is presented with series of choice sets, each with a status quo choice that does not fully reflect their current situation. In both cases, participants are presented with a choice between two alternative hypothetical water service packages: an SQ alternative, representing their current or perceived current water service package, and an 'opt out' option.

The study uses a novel approach in that the sample is split into two strata, with each stratum presented with two choice experiments. The fundamental difference between the two experiments is the SQ option. Results from the two experiments in each stratum are then compared, against each other and against results from the other stratum. By doing this, we can detect the impact and magnitude of the SQ bias on the utility functions and estimated MWTP figures, and the magnitude of this impact. It is common practice for studies that compare estimates across experiments to make comparisons based on the statistical significance, sign and absolute value of the coefficient (see Bateman et al., 2009; Orzechowski et al., 2005; Patterson et al., 2017; Vriens et al., 1998). In these studies, the numbers of statistically significant coefficients in each experiment are compared. The absolute value of the coefficient is used to measure the magnitude of impact a change in an attribute has on the respondents' utility, while the sign of the coefficient gives the direction of the impact. Our study follows this approach in comparing experiments.

The rest of the paper is organised into eight sections. Section 2 reviews the literature on SQ bias. Section 3 gives an overview of the South African water sector. Section 4 discusses the experimental design of the study. Section 5 discusses modelling approaches. Section 6 presents the experimental data. Section 7 presents and discusses the empirical findings. Section 8 concludes the study.

## 2. SQ bias theories

Since the pioneering work of Samuelson and Zeckhauser (1988), SQ bias has received much attention in the literature. Various theories were developed to explain the main causes of SQ bias. Most of these theories fall within the domain of psychology. The most notable theories to explain the origin and drivers of SQ bias include the loss aversion theory, the inertia theory, the decision avoidance theory, and the incomplete preferences theory. All these theories explain the psychological reasons for SQ bias. After the establishment of the SQ bias theories, empirical studies emerged in the literature validating the drivers of SQ bias, as identified earlier in the theoretical literature. This section discusses some of the theories on SQ bias. The empirical literature on SQ bias is also used to explain and discuss the SQ bias theories.

Proposed by Tversky and Kahneman (1991), the loss aversion theory suggests that the SQ option serves as a reference point, and the losses relative to this reference point have greater impact on preferences than gains do. The theory argues that individuals keen to avoid losses have a strong tendency to remain in the SQ, because the disadvantages of leaving it appear larger than the advantages. This argument also holds true when respondents are not sure of the good, or when they face complexity in understanding the given choices. In such cases, respondents choose the SQ, whose utility they currently experience as minimising losses linked to hypothetical utilities from experimentally designed options. The empirical literature identifies various instances in which respondents choose the SQ to avoid loss. The most notable instances include when respondents are faced with complex choice sets, and when too many choice sets, attributes and levels are included (see Meyerhoff and Liebe, 2009; Moon, 2000; Oehlmann et al., 2017; Scarpa et al., 2007). In such cases, respondents tend to choose the default option whose utility they currently experience.

The inertia theory (Ritov and Baron, 1992; Schweitzer, 1994) argues that keeping the SQ requires only inaction, and respondents are known to have some preference for inaction. In this theory, respondents are believed to have an attachment to and persistence in the use of the status quo, even in the presence of better alternatives and/or incentives to change. This is normally the case where the perceived value of change is low, which means respondents may show strong resistance to change. From a rational decision perspective, inertia would be due to loyalty to respondents' current status, or as a result of the respondents trying to minimise their losses. Inertia due to loyalty to the current status is explained in several empirical studies, among them Scarpa et al. (2007) and Dubé et al. (2010). The argument put forward in these studies is that when respondents are loyal to the current status, they are not likely to choose hypothetical alternatives provided in choice sets. In such cases, they tend to choose the SQ option ahead of any other available option.

In the decision-avoidance theory, Anderson (2003) argues that when expected to make a decision between many options, respondents usually choose not to make a decision. This arises when respondents avoid making choices by postponing, or through choosing an easy way that may involve no action or no change (Anderson, 2003). The decision avoidance theory builds on earlier postulates in Beattie et al. (1994), which state that respondents desire to make or avoid decisions independent of any consequence that this may cause. Depending on the context, respondents are therefore assumed to be either decision seeking or decision averse. In explaining the decision avoidance theory, Anderson (2003) acknowledges that marked preferences for avoidant options have been discovered in diverse areas of the literature. The more specific instances include when respondents generally prefer no change (status quo bias, Samuelson and Zeckhauser, 1988), no action (omission bias, Ritov and Baron, 1992; inaction inertia, Tykocinski et al., 1995), or delay (choice deferral, Dhar, 1996).

In the incomplete preference theory, Mandler (2004) argues that respondents who have an unchanging but incomplete preference usually prefer the SQ. The theory suggests that respondents with incomplete preferences choose to maintain the SQ when they follow the simple rule of refusing to trade their endowment for unranked bundles. Such respondents do this while waiting to be offered an alternative that is ranked as superior. This process of refusing to trade their endowment for unranked bundles respects respondents' interests, and respondents will not be led to outcomes they judge to be inferior (Mandler, 2004). Eventually, respondents persistently maintain their SQ. The incomplete preference theory is built on findings from Diamond and Hausman (1994) that respondents with incomplete preferences do not make preference judgements between certain pairs of bundles. This is more prevalent when intangible goods are involved; respondents may not form a definitive view of the monetary value of an incremental unit of a good.

Subsequent to the establishment of these SQ theories, several empirical studies have been conducted on the drivers of SQ bias. In the empirical literature, loyalty to the SQ is commonly identified as a key determinant of SQ bias (see Ren, 2014; Scarpa et al., 2007; Dubé et al., 2010).

When respondents are loyal to the SQ, they tend to stick with the SQ option rather than choosing one of the hypothetical alternatives provided. Marsh et al. (2011) identify respondents' knowledge of the good as another key driver of SQ bias. Respondents who are not completely aware of the good try to avoid the risk associated with choosing hypothetical alternatives. In such situations, respondents maintain the SQ option, as argued in the risk aversion theory (Tversky and Kahneman, 1991) and in the incomplete preference theory (Mandler, 2004). Other notable drivers of SQ bias identified in the empirical literature include protest attitude, attitude towards the good, perceived choice task complexity, number of attributes and levels, and number of choice profiles (see Boxall et al., 2009; Meyerhoff and Liebe, 2009; Oehlmann et al., 2017; Moon, 2000; Ren, 2014; Zhang and Adamowicz, 2011).

Notably – because of the various reasons discussed earlier in this section – SQ bias is inevitable in CEs, though efforts are made to address the problem. Such efforts include omitting the SQ option (see Hensher et al., 2005; Saldías et al., 2016), and using individual-specific SQ options (see Campbell et al., 2008; Hess and Rose, 2009; Marsh et al., 2011). Our study examines whether all these efforts are necessary. It does so by examining whether the presence of SQ bias affects empirical results and welfare measures. One study that has some similarities to our study is Boxall et al. (2009), which examines the impact of SQ bias on welfare measures. In the next section, we discuss the experimental design used in this study.

## 3. The South African water sector

South Africa has a complex water governance environment, with both considerable successes in and significant ongoing challenges to achieving sustainable, adequate and equitable water access (Beck et al., 2016), both of which impact water service levels. Historically, water supply and distribution schemes in South Africa were created and managed during the colonial and apartheid eras to serve predominantly white populations. Investment in aspects such as pipes, dams and other water-related infrastructure were differentially applied in different areas during apartheid, with homelands, townships and informal settlements receiving significantly less funding, and generally a lower quality of water service (Goldin, 2010). This led to access to water services in South Africa being highly differentiated by race and income, as well as an extremely fragmented water management system (Herrfahrdt-Pähle, 2010) and undemocratic participatory engagement, resulting in challenges that are still experienced today.

The South African water sector is an ideal subject for a case study, due to the fragmentation that has resulted in a differentiated water service. We chose to conduct our experiments in Durban because of its unique characteristics. Although Durban is South Africa's third-biggest city, it is unique in that it is the only city that has some township/informal settlement, some suburban, and some rural components. This last is uncommon in cities and towns in South Africa. The profile of the city implies that the level of water service is not uniform, which makes it ideal for our experiment. Water provision in each area of South Africa is the responsibility of the area municipality, which also acts as a water utility. They are commonly referred to as Water Service Authorities (WSAs). WSAs are responsible for the provision of water services within their area of jurisdiction. A WSA may carry out the functions of a water services provider (WSP) itself, or it may sub-contract the delivery to a third party. For Durban, the eThekwini Metropolitan municipality is the WSA, as well as being a WSP (see the map of eThekwini below).


**Figure 1:** Map of the eThekwini Metropolitan Municipality

**Source:** Local Government Handbook (2012)

Durban is in the eastern part of South Africa, in the province of KwaZulu-Natal (KZN). The municipality has a population of about 3.6 million people (eThekwini Municipality, 2015). Figure 1 shows suburban, township and rural areas in the municipality. Due to the apartheid history of segregation, there are townships for black South Africans and townships for Indian South Africans. The former includes areas such as KwaMashu, Inanda, Clermont and Umlazi, while the latter includes Chatsworth and Phoenix. Rural areas in the municipality include Umbumbulu, and areas such as Umhlanga, Verulam and Westville are suburbs. Township areas are densely populated relative to suburban areas. For example, the 2011 National Census shows that the total population in KwaMashu was 175 663 people (50 683 households), Inanda had 178 418 people (44 736 households), Umlazi had 404 811 people (104 914 households) and Chatsworth had 196 580 people (54 497 households). These numbers are much larger than those reported for suburban areas such as Umhlanga (24 238 people and 9 256 households), Verulam (37 273 people and 10 896 households) and Westville (30 508 people and 8 814 households)[4].

The minimum standard of water service provided by the municipality is a community tap designed to serve a community where the maximum distance from the furthest dwelling should not be greater than 200 metres (eThekwini Municipality, 2014). However, such facilities are mostly found in informal settlements (e.g. Bhambayi, close to Inanda township, has community taps). The 2011 National Census revealed that while 60.2% of households in the municipality had access to piped water services inside their dwellings, about 17% obtained potable water from community taps. Where households do not access potable water from inside the dwelling or from a community tap, they receive it through a tap in the yard, a phenomenon common mostly in townships. Based on statistics from the 2011 National Census, the percentage of suburban households accessing piped water inside the dwelling was 99% for Umhlanga, 94% for Westville and 81% for Verulam. The same statistics in the townships were 50% in Umlazi, 35% in Inanda and 44% in KwaMashu.

The municipality uses an increasing block tariff (IBT) pricing structure to charge for water services. IBT is a volumetric tariff system proportional to consumption (i.e. it increases with consumption). IBT is used in South African municipalities as a measure to address the problems of unequal income distribution, by providing fair access to water in a country that has huge income disparities (Banerjee et al., 2010; Jansen and Schulz, 2006; Muller, 2008). In line with the

[4] These statistics are based on the 2011 National Census data published by Statistics South Africa.

country's Free Basic Water Policy of 2002, which states that indigent households should receive at least 6 000 litres of free water per month, the eThekwini municipality provides 9 000 litres free to each of its indigent households. To determine who is indigent, the municipality uses a property value-based targeting approach in which households occupying properties valued at less than R250 000 (i.e. $17 483) are considered indigent and qualify for free basic water services. Such property values are predominantly found in townships, informal settlements and rural areas; hence, most recipients of free basic water services are from these areas.

Due to budget constraints, we could not collect data from all areas of the municipality as illustrated in Figure 1. Various areas were selected based on their population size, demographic representation, geographical location and economic status. The suburban areas surveyed were Morningside, Musgrave and Overport in central Durban, as well as La Lucia, Umhlanga, and Verulam in northern Durban. For townships, data was collected from Inanda, Ntuzuma and Phoenix in northern Durban, as well as Chesterville, Chatsworth and Umlazi in southern Durban. Respondents from informal settlements in Bhambayi and Umlazi were also surveyed. Rural households were surveyed in Umbumbulu.

The sampled areas were selected for three main reasons. First, they represent the suburbs, townships, informal settlements and rural areas that are the true spatial segmentations of the study area. Second, our sampled areas represent areas where different racial groups reside. For example, Phoenix and Chatsworth represent townships where Indian South Africans reside predominantly, while the other townships represent areas that are predominantly occupied by black South Africans. These two racial groups are the most dominant in townships and other low-income areas. Third, the sampled areas represent the northern, central and southern parts that form the geographic demarcations of Durban. An exploration of these diverse areas gave us a clear picture of the range of water service packages in the municipality. Since access to water in townships is very similar to access in informal settlements and rural areas, we grouped these segments together into one sub-sample.

## 4. Experimental design

CEs are conducted to determine the independent influence of different attributes on the choices that are observed to be made by sampled respondents. The first step in CE modelling is selecting relevant and realistic attributes. Attributes are translated features and characteristics that show the objective properties of a commodity. These can be deduced from literature reviews, focus group discussions, pilot studies and expert consultations. After attributes are selected, feasible, realistic, and non-linearly spaced levels that span the range of respondents' preference maps are assigned to each attribute (Hanley et al., 2001; Louviere et al., 2000). The attributes and levels are then experimentally designed into various choice profiles. Hensher et al. (2015) describe experimental design as the effect on a response variable following the specialised manipulation of the levels of one or more other variables. This section discusses the attributes and levels used in the study, as well as how they are designed into choice profiles.

### *4.1. Attributes and levels*

This study tests the impact of SQ bias using a case of household preference for water service packages in one of South Africa's municipalities. Water provision is deemed an ideal case study, because the diversity and complexity found within South African municipalities makes it difficult to come up with an SQ that applies to the whole population. Although the quality of water received by different households in different areas of the same municipality may be similar, the total package of the water service may differ in terms of location of tap, reliability of supply, water pressure, and monthly household water bill. To determine the attributes and levels for the study, two focus groups were established. One focus group contained residents from the suburbs, while the other had residents from townships. Through focus group discussions and a review of the literature, it emerged that households are concerned about the position of the tap, the reliability of the supply, the pressure, quality and cost of water services. Collectively these features make up a typical water service package; and are adopted as attributes in this study. The final attributes and levels are presented in Table 1.

**Table 1:** Attributes and levels used in the study

| Attribute | Description | Attribute Levels |
|---|---|---|
| **Piped water**<br> | Access to piped or tap water in the dwelling, on-site or off-site. This shows how piped water is delivered to households. | **Level 1:** Inside dwelling<br>**Level 2:** In yard<br>**Level 3:** Community tap: less than 200m from dwelling<br>**Level 4:** Community tap: more than 200m from dwelling<br>**Level 5:** No access to piped water |
| **Reliability of supply**<br> | Whether the household had any interruption in piped water supply in the last month. | **Level 1:** Yes<br>**Level 2:** No |
| **Water pressure**<br> | Pressure is the force that pushes water through pipes. Water pressure determines the flow of water from the tap. | **Level 1:** High water pressure<br>**Level 2:** Low water pressure |
| **Water quality**<br> | A measure of the suitability of water for a use. Based on selected physical, chemical and biological characteristics. | **Level 1:** Safe to drink<br>**Level 2:** Has colour<br>**Level 3:** Has a taste<br>**Level 4:** Has a smell |
| **Cost**<br> | Cost per month[5]. | **Level 1:** R120<br>**Level 2:** R220<br>**Level 3:** R400<br>**Level 4:** R680<br>**Level 5:** R980 |

[5] To develop levels for the cost attribute, the current domestic water tariff structure published by the municipality was used. The water tariff structure has five successive and increasing blocks, and the average costs in each block were used as levels for the cost attribute. For the position of the tap (indicated here as the piped water attribute), the literature shows that the main access points for piped water in the municipality are inside the dwelling, in the yard, or community taps.

The attributes and levels presented in Table 1 were used to generate the choice profiles used in the study. As mentioned earlier, various classes of experimental design exist in the literature. Each of these classes has its own merits and demerits. An analysis of each of the classes of experimental design is essential before one adopts a class for designing choice profiles. In the next sub-section, the study presents a brief discussion of the classes of experimental design that are commonly used in the CE literature. The sub-section also explains the class of design adopted in this study, its advantages over the other classes of designs, and how the attributes and levels presented in Table 1 were designed into choice profiles used to collect stated preference data for the study.

### *4.2. Choice experiment design*

This study uses an efficient design to create the hypothetical choice sets. Efficient designs produce more robust data, which leads to more reliable parameter estimates with even lower sample sizes and smaller widths in the confidence intervals (Rose and Bliemer, 2009). Using efficient designs requires some knowledge of prior parameters. Where prior parameters are not known, designers can draw them using the Bayesian parameter distributions (Bliemer et al., 2008). These are less sensitive to misspecification of priors, because they assume prior parameter values to be approximately known and randomly distributed. To determine the number of draws for Bayesian priors, the Gaussian method can be used, and the rule of thumb for the absolute minimum Gaussian quadrature is $2^K$, where $K$ is the number of Bayesian priors (Rose and Bliemer, 2009). To allow for a more efficient design our study used the maximum possible Gaussian draws (i.e. 32 draws). When Bayesian parameter distributions are used to draw prior parameters, the design becomes a Bayesian D-*error* design (i.e. $D_b$-*efficient*). This is commonly used in efficient designs where the true population parameters are not known with certainty.

Using the attributes and levels presented earlier in Table 1, six choice sets of two profiles each were generated by means of a normally distributed Bayesian D-*efficiency* method. Two experiments were designed for each of the two sub-samples. The first experiment contains an SQ that resonates with each sub-sample, while the second experiment contains an SQ that is partially relevant to each sub-sample. Each experiment has six choice sets, each of which consists of four options: an SQ option, Options 1 and 2, and a 'None' option. The 'None' option was included as a way of giving respondents room to opt out. Including an opt-out option is essential, as it gives respondents the chance not to select any of the given alternatives. If the opt-out option is not given, respondents are forced to choose between their SQ and the hypothetical, experimentally designed options. If a respondent prefers neither the SQ nor the experimentally designed alternatives, incorrect inferences will be deduced if an opt-out option has not been included. An example of a choice set with an SQ relevant to the township stratum is shown in Table 2.

**Table 2:** Example of a choice set with an SQ relevant to the township sub-sample

| | **STATUS QUO** | **ALTERNATIVE 1** | **ALTERNATIVE 2** | **NONE** |
|---|---|---|---|---|
| **Piped water** | In yard | In yard | Inside dwelling | |
| **Reliability** | No | Yes | No | |
| **Water pressure** | Low pressure | Low pressure | High pressure | |
| **Water quality** | Safe to Drink | Has colour | Has a smell | |
| **Monthly cost** | R0 | R120 | R400 | |
| **I WOULD CHOOSE:** | ☐ | ☐ | ☐ | ☐ |

The SQ presented in Table 2 was the baseline that resonated with most of the township dwellers. As argued first in Samuelson and Zeckhauser (1988) and in many subsequent studies, we expected most respondents to choose the SQ option in the experiment that presented them with their own SQ. However, since the main purpose of this study is to test whether SQ bias affects empirical results, we presented the township respondents with a second experiment. The second experiment contained an SQ option perceived to be less relevant to the township sub-sample.

By presenting the township stratum with a second experiment containing a partially relevant SQ, we can test whether utility functions and MWTP estimates differ across experiments. The difference between the first and second experiments is mainly in the SQ options. Therefore, we expect less SQ bias in the experiment in which the SQ was less relevant. This is because respondents may view the SQ option as one of the experimentally designed options. Psychological literature implies that if respondents are made to choose between their current SQ and other hypothetical options, they tend to disproportionately choose the SQ option. Reasons for this bias selection have been given in Samuelson and Zeckhauser (1988) and subsequent theories (see Tversky and Kahneman, 1991; Ritov and Baron, 1992; Anderson, 2003; Mandler, 2004). An example of a choice set with an SQ perceived to be less relevant to the township sub-sample is given in Table 3.

**Table 3:** Example of a choice set with an SQ partially relevant to the township stratum

| | STATUS QUO | ALTERNATIVE 1 | ALTERNATIVE 2 | NONE |
|---|---|---|---|---|
| **Piped water** | No access to piped water | Inside dwelling | In yard | |
| **Reliability** | Yes | No | Yes | |
| **Water pressure** | High pressure | High pressure | Low pressure | |
| **Water quality** | Bad Taste | Has a smell | Safe to drink | |
| **Monthly cost** | R0 | R680 | R220 | |
| **I WOULD CHOOSE:** | ☐ | ☐ | ☐ | ☐ |

The same approach explained above for the township sub-sample was also applied to the suburban sub-sample. Respondents in the suburban sub-sample were also presented with two experiments. The first experiment contained a baseline SQ option perceived to be relevant to the sub-sample, while the second experiment presented respondents with an SQ option perceived as less relevant to them. As with the township sub-sample, we anticipated SQ bias in the first experiment and real trade-offs in the second. Utility functions and MWTP estimates from each of these two experiments will be compared against each other, as well as against those from the township stratum.

## 5. Modelling

The theoretical foundation of choice experiments arose from the random utility theory, which hypothesises that an individual makes choices based on the characteristics of the good, along with a random component (McFadden, 1974). According to Ben-Akiva and Lerman (1985), the random component could emerge from the uniqueness of the individual's preferences, or due to researchers having incomplete information about the individual observed. Given this, the random utility theory hypothesises that the utility $U_{ij}$ of individual $i$ obtained from alternative $j$ is not known but can be decomposed into a deterministic component $V_{ij}$ and an unobserved random component $\varepsilon_{ij}$. Therefore, the individual utility function will be presented as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

Equation 1 is the basic utility function, which could alternatively be expressed by decomposing the indirect utility function for individuals into the deterministic component $V_{ij}$, which is normally specified as a linear index of the attributes in a choice set, and a stochastic component $\varepsilon_{ij}$, representing the error term. Therefore, the function assumes the form:

$$U_{ij} = V_{ij}\left(X_{ij}, C_{ij}, \beta\right) + \varepsilon_{ij} \tag{2}$$

Parameter $U_{ij}$ is the true but unobservable utility of individual $i$ associated with alternative $j$, while $X_{ij}$ is a vector of the attributes associated with alternative $j$, parameter $C_{ij}$ is the cost of alternative $j$, parameter $\beta$ is a vector of preference parameters for the population in the sample, and $\varepsilon_{ij}$ is the stochastic component (random term) with a zero mean. The random utility theory assumes that any rational individual $i$ will choose alternative $j$ over alternative $k$ if $U_{ij} > U_{ik}$. Each alternative consists of a bundle of attributes. When one alternative is selected over the other, it suggests that the hypothetical utility derived by an individual from the chosen alternative is greater than the utility of the other alternative not chosen (Greene, 2003, Hensher et al., 2015). This is expressed as follows:

$$P_i(j) = \text{Prob}\left(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}\right) \forall\, k \in C, k \neq j. \tag{3}$$

If the error terms are independently and identically distributed (IID) with an extreme value type I distribution, the variance of which is $var(\varepsilon) = \pi^2\tau^2/5$, where $\tau$ is a scale parameter used to normalise the model, then the choice probability of an alternative is expressed as:

$$P_{ij} = \exp\left(\frac{v_{ij}}{\tau}\right) / \sum_{k=1}^{K} \exp\left(\frac{v_{ik}}{\tau}\right) \tag{4}$$

The basic conditional logit model (CLM) – also known as the multinomial logit (MNL), in cases where there are no choice varying attributes – assumes the choice probability illustrated in equation 4. Historically, for many years the MNL model was the primary basis for the analysis of multinomial choices (Keane and Wasi, 2012). However, the model is criticised because it assumes respondents to have homogeneous tastes for observed attributes and that the random part of utility obeys the independence from irrelevant alternatives (IIA) as well as the independence and identical distribution (IID) properties. These assumptions rule out persistent heterogeneity in taste for both observed and unobserved product attributes (Hensher et al. (2015). Therefore, more advanced models such as the nested logit (NL), the mixed logit (MXL – also called the Random Parameter or RPL), the generalised mixed logit (GMXL), and the non-linear random parameters logit (NRPL) models are suggested in the discrete choice analysis literature. (see Greene, 2012; Hensher et al., 2015). This study uses the MXL and GMXL models.

MXL allows coefficients to vary randomly across individuals, accounts for both observed and unobserved heterogeneity in the preference parameters and can use single cross-sectional data as well as panel data (Hensher and Greene, 2003; Hensher et al., 2005; Hensher et al., 2015). Its model formulation is a one-level MNL model for individuals $i = 1, \dots, N$ in choosing alternative $j$, breaking down coefficients into a population mean and an unobserved individual's deviation from that mean. This is shown as:

$$U_{ij} = \beta_1 X_{ij} + \varepsilon_{ij} = \beta X_{ij} + \eta_{ij} + \varepsilon_{ij} \tag{5}$$

Parameter $\beta_1$ is the population mean and $\eta_{ij}$ is the individual deviation from the population mean (i.e. the individual specific heterogeneity, with mean zero and standard deviation one, according to Greene (2012)). MXL models are good at identifying taste heterogeneity only. There is growing interest from researchers in accounting for scale heterogeneity across individuals.

The GMXL model recognises the relationship between scale and taste heterogeneity (Fiebig et al., 2010; Hensher et al., 2015; Keane and Wasi, 2012). It builds on the specifications of MXL and the generalised multinomial logit (GMNL) model suggested by Fiebig et al. (2010). The essential format of the GMXL model is a mixed logit model, illustrated as:

$$U_{ij} = \boldsymbol{\beta}_i' \mathbf{x}_{ij} + \varepsilon_{ij} \tag{6}$$

$$\boldsymbol{\beta}_i = \sigma_i \boldsymbol{\beta} + [\gamma + \sigma_i(1-\gamma)]\boldsymbol{\Gamma}\mathbf{w}_i,\ \mathbf{w_1} \sim \mathrm{N}[\mathbf{0}, \mathbf{I}], 0 \le \gamma \le 1 \tag{7}$$

$$\sigma_i = \exp\left(-\frac{\tau^2}{2} + \tau \mathrm{v}_i\right), \mathrm{v}_i \sim \mathrm{N}[0,1] \tag{8}$$

Equation 7 is an MNL model based on the extreme value distribution of the error component $\varepsilon_{ij}$. The general form of the GMXL model combines the scaled MNL model with the random parameter model. A random scaling factor $\sigma_i$ with mean 1 and variance $\exp(\tau^2 - 1)$ is included in the model. Greene (2012) and Hensher et al. (2015) suggest that Gamma $\gamma$ is central to the GMXL model, as it controls the relative importance of the overall scaling of the utility function. When $\gamma$ = 0, it implies a scaled MXL model, while when $\gamma$ = 1 it means a hybrid model. The other important element of the GMXL model is the Tau scale $\tau$. When $\tau$ is equal to zero ($\tau = 0$), it implies that $\gamma$ is not identified (that is, $\gamma$ is not estimable).

Additionally, the study estimates the marginal willingness to pay (MWTP) for the water service attributes. It is deemed essential to also examine the impact of SQ bias on welfare measures. This is because it could be possible for SQ bias to have an impact on the utility functions, but not have any impact on welfare measures, and vice versa. Hensher et al. (2015) suggest that one important output from choice models is the MRS between specific attributes of interest, with a financial variable typically being in the trade-off so that MRS is expressed in monetary terms. MWTP gives the average estimates of what households are prepared to pay for or against improvements in each attribute. Assuming a linear utility function with attribute $X$ and a cost $C$:

$$U_{ij} = \beta X_j + \mu\left(C_i - p_j\right) + \varepsilon_{ij} \tag{9}$$

$U_{ij}$ is the utility of the respondent $i$ for alternative $j$; while $\beta_j$ and $\mu$ are the marginal (dis)utilities of attribute $X$ (attribute of interest) and cost, respectively. MWTP is a simple ratio of the coefficients which can be compared across models because the scale parameters are cancelled. Dikgang and Muchapondwa (2014) point out that it is possible for researchers to use a set of observed discrete choices to determine different marginal values for each attribute used in explaining the policy alternatives, instead of a single value for the whole policy scenario. As such, this current study follows that route of determining the marginal values for each attribute.

## 6. Experimental Data

### *6.1. Data collection*

The study is based on experimental data collected from 999 household heads from Durban during the period September to November 2016. Survey instruments were prepared in English, and four enumerators fluent in both English and isiZulu (i.e. the local language) were recruited from a group of postgraduate students. These enumerators were trained and supervised during the data collection process. A total of 500 responses was collected in the suburbs, while 499 were collected in townships. Responses from the suburbs were further divided into 249 collected using a questionnaire with a relevant SQ (block 1), and 251 collected using a questionnaire with a partially relevant SQ (block 2)[6]. For the township sub-sample, 250 complete responses were collected in block 1 and 249 in block 2. Choice experiments allow even smaller samples to produce many observations. This is because each respondent is asked repetitively, which then increases the number of observations.

When collecting data, households were conveniently selected until the required data points from each area were obtained. To avoid fatigue and receive maximum cooperation, each respondent took part in only one experiment. For example, if the first respondent in the township sub-sample took part in an experiment using the SQ perceived to be relevant, the next respondent would then take part in the experiment with the SQ perceived as less relevant. In addition to the choice experiments, each of the four questionnaires contained two other sections. The second section collected general information, while the third section collected biographic details. Except for the question on household monthly income, which had higher values in the suburbs sub-sample, all the questions in the second and third sections were similar across the four questionnaires (i.e. respondents answered the same questions in these sections).

### *6.2. Descriptive statistics*

In addition to stated preference data, the collected data included detailed information on the demographic characteristics of the respondents, as well as some general information on how the respondents received water services at the time. The demographic characteristics collected included household size, level of education, age and income, as well as source of income. In addition to these demographic data, some general information was collected on how each household accessed piped water services, whether they received free basic water, how often they experienced water interruptions, and how they perceived the quality of water they received. Such

[6] Henceforth, the experiment involving a relevant SQ will be identified as block 1, while the experiment with the partially relevant SQ will be identified as block 2. It is important to note that each sub-sample has both blocks.

information is deemed to be essential, as it determines households' preferences for water service packages. Table 4 provides an overview of the descriptive statistics of the main variables of interest for all blocks in the two sub-samples.

**Table 4:** Descriptive statistics of respondents

| | Suburbs | | Townships | |
|---|---|---|---|---|
| | Block 1<br>Mean (SD) | Block 2<br>Mean (SD) | Block 1<br>Mean (SD) | Block 2<br>Mean (SD) |
| ***No. of respondents (N)*** | ***249*** | ***251*** | ***249*** | ***250*** |
| Female respondents (%) | 41 (49) | 41 (49) | 44 (51) | 45 (48) |
| Household head (%) | 39 (49) | 45 (50) | 49 (50) | 55 (50) |
| Average household size | 4 (2) | 4 (2) | 5 (3) | 5 (3) |
| Married respondents (%) | 51 (50) | 45 (50) | 29 (45) | 34 (47) |
| Race (%): *African* | 42 (49) | 41 (49) | 87 (33) | 79 (41) |
| *Indian* | 45 (50) | 43 (50) | 12 (33) | 20 (40) |
| *Coloured* | 5 (22) | 6 (23) | 1 (6) | 1 (6) |
| *White* | 7 (26) | 10 (51) | 0 | 1 (6) |
| Age (%): *16-24 years* | 12 (33) | 14 (35) | 15 (36) | 20 (40) |
| *25-34 years* | 32 (47) | 37 (48) | 24 (43) | 23 (42) |
| *35-44 years* | 24 (43) | 25 (44) | 21 (41) | 22 (41) |
| *45-54 years* | 14 (34) | 14 (35) | 14 (35) | 15 (36) |
| *55-64 years* | 12 (33) | 6 (24) | 12 (33) | 11 (31) |
| *65+ years* | 6 (23) | 4 (19) | 12 (33) | 10 (30) |
| Secondary education and above (%) | 76 | 74 | 30 | 32 |
| Monthly income (%): | | | | |
| *<R2500* | - | - | 75 (43) | 67 (47) |
| *R2500 < R5000* | - | - | 14 (34) | 18 (39) |
| *R5000 < R10000* | - | - | 9 (28) | 10 (31) |
| *>R10000 < 15000* | 52 (50) | 46 (50) | 2 (14) | 4 (20) |
| *R15000 < R30000* | 31 (46) | 30 (46) | - | - |
| *R30000 < 50000* | 12 (32) | 14 (35) | - | - |
| *>R50000* | 6 (23) | 10 (30) | - | - |
| Recipients of free basic water (%) | - | - | 39 (49) | 66 (47) |
| Access to piped water (%): | | | | |
| *Inside dwelling* | 100 (6) | 100 (11) | 71 (46) | 77 (42) |
| *In yard* | 0 | 0 | 25 (43) | 19 (39) |
| *Community tap* | 0 | 0 | 4 (20) | 4 (19) |
| Water supply interruptions (%): | | | | |
| *Very often* | 8 (28) | 6 (23) | 21 (41) | 24 (43) |
| *Once in a while* | 53 (50) | 51 (50) | 69 (46) | 62 (49) |
| *Not at all* | 38 (49) | 43 (50) | 10 (30) | 14 (35) |
| Water quality experiences (%): | | | | |
| *Not clear* | 35 (48) | 24 (43) | 29 (45) | 34 (48) |
| *Bad taste* | 3 (18) | 4 (19) | 1 (8) | 2 (14) |
| *Bad smell* | 0 (6) | 1 (28) | 0 | 0 |
| *Has colour* | 12 (33) | 7 (35) | 2 (14) | 2 (14) |
| *Good quality* | 50 (50) | 65 (48) | 68 (47) | 62 (49) |

*Note: Standard deviations are reported in parentheses.*

Table 4 shows various systematic differences between the suburbs and township sub-samples. It is noted that the average household size is slightly lower in the suburbs sub-sample with a mean of 4 family members, compared to the townships sub-sample where the average household size is 5 family members. This dynamic reflects the actual trends in South African communities, where township families usually include extended family members. It is also noted that most township dwellers are black South Africans, at around 80%, reflecting the legacy of a segregated past in which non-white South Africans were confined to township areas. However, it is equally important to note that although South Africans of Indian origin constitute the greatest number of suburban dwellers, many black South Africans also live in the suburbs. Another important dynamic noted in the table is that most of the respondents from the suburbs sub-sample have at least secondary-school education. Statistics for this variable sit at above 70% in the suburbs sub-sample, while in the township sub-sample the percentage is around 30%.

In terms of access to piped water, all households in the suburbs sub-sample access piped water inside their dwellings, while the percentage of households with such a facility in the township sub-sample is around 70%. Households without piped water inside their dwellings access it mostly from the yard, while about 4% of the township households surveyed still access piped water from community taps. These statistics reflect that some township households receive inferior water service packages compared to suburban households. However, it is imperative to note that overall, most respondents in the sample indicated that they receive water of good quality, even though some respondents suggested that the water they receive is not clear. The satisfaction with water quality across all sub-samples clearly indicates that even though households may access water differently, the quality of the water is good. Finally, although households from all sub-samples experience water interruptions "once in a while", more interruptions are experienced by the township sub-sample than by the suburbs sub-sample.

### *6.3. Frequency distribution of stated preference choices*

An understanding of the stated preference data collected using the different experiments is essential. Prior to the survey, we hypothesised that if respondents were presented with their relevant SQ, most of them would choose the SQ ahead of hypothetical designed options, as suggested in Samuelson and Zeckhauser (1988). Probable reasons for this behaviour have been discussed in the previous sections of this study, and include loyalty to the SQ, choice task complexity, loss aversion, inertia, and many others (see Anderson, 2003; Dubé et al., 2010; Lanz and Provins 2015; Mandler, 2004; Meyerhoff and Liebe, 2009; Moon, 2000; Oehlmann et al., 2017; Ritov and Baron, 1992; Scarpa et al., 2007; Tversky and Kahneman, 1991). Therefore, we expected to observe SQ bias in block 1 experiments, where respondents were presented with their realistic SQ option. Furthermore, we expected less SQ bias in block 2 experiments, where respondents were presented with unrealistic SQ options. To explain this phenomenon, Figure 2 presents the frequency distribution of choices across the different options in each experiment.

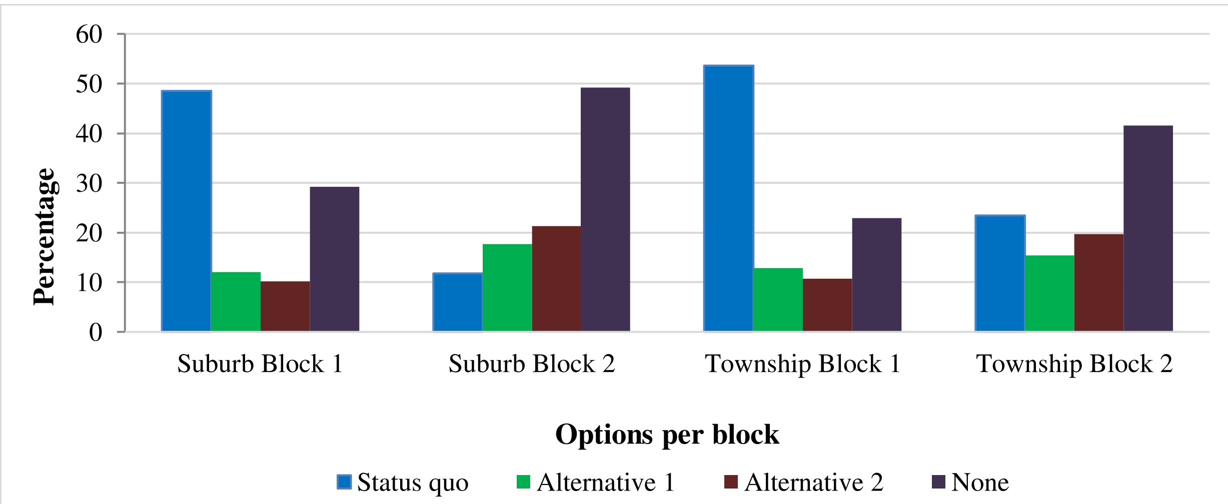


**Figure 2:** Frequency distribution of choices made by respondents

The frequency distribution statistics presented in Figure 2 confirm our hypothesis that most respondents would choose the SQ option if presented with a relevant SQ. This is shown in the number of respondents who chose the SQ options in the first blocks of the two sub-samples. In suburbs block 1, close to 50% of respondents chose the SQ option; while in the township sub-sample, more than 50% of respondents chose the SQ option in block 1. However, in the second blocks of each sub-sample, where respondents were presented with partially relevant SQ options, the frequency of SQ choices was lower than that observed in the block 1 experiments. For the suburbs sub-sample, about 11% of respondents chose the SQ option in block 2; while in the townships sub-sample, around 23% of respondents chose the SQ option in block 2. Interestingly, it is also noted that when presented with a partially relevant SQ option, relatively large numbers of respondents chose to opt out, by selecting the 'none' option. About 49% of the respondents opted out in suburbs block 2, while around 41% of township respondents opted out in block 2.

However, since all options in the choice sets were selected, it is still possible to achieve real trade-offs. As such, the next section presents estimations results from the econometric analysis of stated preference data.

## 7. Empirical findings

To examine the impact of SQ bias on empirical estimates, we use the MXL and GMXL models as estimation tools. The robustness of each of these tools in so far as our data is concerned is compared, and the most fit tool is adopted. Although GMXL is more advanced and is expected to perform better than MXL, Hensher et al. (2015) suggest that the latter may perform better, depending on the dataset. The model that performs best is subsequently used to estimate utility functions. Since our sample is stratified into two sub-samples, and each sub-sample responds to two survey instruments, we estimate utility functions for each sub-sample. MWTP will also be estimated for each sub-sample, using the model that fits best. The ultimate rationale for these two important analyses is to compare estimates across sub-samples and see if there are variations in terms of statistical significance, sign and magnitude of parameter estimates.

To estimate utility functions, the study adopts unconstrained MXL and GMXL models that do not control for heterogeneity in the means of normally distributed random parameters. The five attributes of the study are modelled as normally distributed random parameters while alternative specific constants (ASCs) and socioeconomic characteristics are modelled as fixed parameters. Results are obtained using the Halton sequence for simulation based on 200 draws. Additionally, this section also presents MWTP estimates for each sub-section. The MWTP estimates are then compared across blocks and sub-samples.

### *8.1. Goodness of fit: MXL versus GMXL models*

Since each of the two sub-samples has two blocks, presenting estimation results for both the MXL and GMXL models may lead to too many columns that might render the work clumsy. Consequently, we assess the goodness-of-fit parameters of the two estimation tools. The better-performing tool is adopted, and its results presented. The three main goodness-of-fit statistics commonly used to compare models in the literature are the log likelihood function (LL), Akaike information criterion (AIC), and Bayesian information criterion (BIC). A model with a larger LL estimate is deemed more robust. For AIC and BIC, the model to be preferred is one with the lowest value (see Aho et al., 2014; Akaike, 1998; Burnham and Anderson, 2004). Goodness-of-fit results for the MXL and GMXL models used in this study are presented in Table 5.

**Table 5:** Goodness of fit statistics

| | MXL Model | | | | GMXL Model | | | |
|---|---|---|---|---|---|---|---|---|
| | **Suburb** | | **Township** | | **Suburb** | | **Township** | |
| | **Block 1** | **Block 2** | **Block 1** | **Block 2** | **Block 1** | **Block 2** | **Block 1** | **Block 2** |
| LL | -1117.0 | -1528.7 | -1640.5 | -1786.9 | -525.6 | -1132.0 | -965.9 | -1195.5 |
| AIC | 2270.0 | 3093.5 | 3316.9 | 3609.8 | 1111.2 | 2324.1 | 1991.8 | 2451.1 |
| BIC | 2365.4 | 3189.2 | 3412.4 | 3705.4 | 1270.3 | 2483.6 | 2150.9 | 2610.4 |
| N | 1485 | 1505 | 1484 | 1498 | 1485 | 1505 | 1484 | 1498 |

As hypothesised, the estimates for goodness-of-fit parameters presented in Table 5 show that all GMXL models performed better than the MXL models. Under the GMXL models, the LL estimates for both suburbs and townships are larger than those presented under the MXL models. The GMXL estimates also show lower AIC and BIC statistics than those recorded in the MXL models, implying that the GMXL models outperformed the MXL models. Therefore, we present empirical results from the GMXL models only.

*8.2. GMXL model estimates*

Using unconstrained GMXL models, this study estimates utility as a function of normally distributed attributes. Utility functions for all blocks in each sub-sample assume the form:

$$U_{ij} = ASC + \beta_1 PIPE_{ij} + \beta_2 RELIABILITY_{ij} + \beta_3 PRESSURE_{ij} + \beta_4 QUALITY_{ij} + \beta_5 COST_{ij} + \varepsilon_{ij} \quad (10)$$

ASC in equation 10 is the alternative specific constant, which in the choice experiment literature is often used to capture SQ bias (see Boxall et al., 2009; Lanz and Provins, 2015; Meyerhoff and Liebe, 2009; Oehlmann et al., 2017; Ortoleva, 2010). In studies that test for the existence of SQ bias, the common approach is to include at least two ASCs; one for the status quo option, ($ASC_{SQ}$)

and the other for experimentally designed options. Such studies report a positive and statistically significant $ASC_{SQ}$ as evidence of SQ bias (see Kahneman et al., 1991; Korobkin, 1997; Maltz and Romagnoli, 2015; Meyerhoff and Liebe, 2009). However, our study does not primarily seek to capture the existence of SQ bias.

This study notes and acknowledges the existence of SQ bias, and tests whether respondents' preferences change when they are presented with experiments containing different SQ options. This is done by examining the sign, significance and magnitude of the attribute parameters in the utility functions from each block of the two sub-samples. Therefore, although this study also reports on the sign and significance of the ASC estimates across sub-samples, the main emphasis will not be on the existence of SQ bias, but on its impact on the utility function. A comparison of attribute parameter estimates in each utility function informs us whether preferences differ with changes in the SQ. Table 6 presents the estimation results.

**Table 6:** Estimation results based on GMXL models

| | Suburbs | | | | Townships | | | |
|---|---|---|---|---|---|---|---|---|
| | Block 1 | | Block 2 | | Block 1 | | Block 2 | |
| | Par. Est. | Std. Err | Par. Est. | Std. Err | Par. Est. | Std. Err | Par. Est. | Std. Err |
| **Random parameters in utility functions** | | | | | | | | |
| COST | 0.010*** | 0.003 | -0.005* | 0.002 | -0.018*** | 0.003 | -0.013** | 0.005 |
| PIPE | -4.229 | 3.180 | -2.726*** | 1.045 | 0.376 | 0.436 | 0.206 | 0.259 |
| RELIABILITY | -3.570 | 2.690 | 1.166 | 1.129 | 0.826 | 0.814 | -0.003 | 0.732 |
| PRESSURE | 5.255* | 2.373 | 5.645** | 2.555 | 0.606 | 0.997 | -0.615 | 0.914 |
| QUALITY | -10.190* | 5.954 | -11.111** | 4.790 | -3.799*** | 0.691 | -3.419** | 1.470 |
| **Nonrandom parameters in utility functions** | | | | | | | | |
| $ASC_{SQ}$ | 11.707*** | 1.435 | 2.566** | 0.869 | 3.674*** | 1.590 | 2.516** | 0.942 |
| $ASC_{1\ and\ 2}$ | 6.905* | 1.922 | 3.463*** | 0.302 | 5.815** | 1.603 | 3.822*** | 0.912 |
| AGE | -0.924 | 0.563 | -0.084 | 0.227 | -0.264 | 0.300 | -0.287* | 0.163 |
| EDUCATION | -0.284 | 0.338 | -0.084 | 0.103 | -0.447** | 0.216 | 0.064 | 0.141 |
| GENDER | -1.176 | 1.413 | -0.596 | 0.433 | 0.978 | 0.682 | -1.452*** | 0.531 |
| INCOME | -1.163 | 0.773 | 0.762*** | 0.261 | -0.255 | 0.385 | -0.326 | 0.268 |
| RACE | 0.104 | 0.778 | -0.541** | 0.234 | -0.009 | 0.430 | 0.144 | 0.271 |
| STATUS | 2.414 | 1.552 | -0.539 | 0.525 | -0.389 | 0.858 | 0.067 | 0.507 |
| **Diagonal values in Cholesky matrix, L.** | | | | | | | | |
| NsCOST | 0.003 | 0.003 | 0.012** | 0.005 | 0.017*** | 0.003 | 0.011** | 0.004 |
| NsPIPE | 0.792 | 2.231 | 4.301** | 1.749 | 1.972*** | 0.529 | 2.186** | 0.883 |
| NsRELIABILITY | 2.405** | 1.142 | 1.300 | 1.210 | 2.392*** | 0.840 | 0.759 | 0.742 |
| NsPRESSURE | 0.373 | 1.334 | 4.527** | 2.166 | 0.923** | 0.372 | 4.026** | 1.627 |
| NsQUALITY | 3.768** | 1.557 | 5.077*** | 1.898 | 0.306 | 0.456 | 1.742* | 0.903 |
| **Below diagonal values in L matrix. V = L*Lt** | | | | | | | | |
| PIPE:COST | -1.419 | 1.840 | -0.913 | 0.620 | -2.265*** | 0.465 | -1.877*** | 0.715 |
| RELIA:COST | -2.918 | 2.045 | 5.218** | 2.482 | -1.189 | 0.821 | 0.797 | 0.674 |
| RELIA:PIPE | -2.568 | 2.410 | -1.388 | 1.305 | -3.228*** | 1.163 | -3.250** | 1.488 |
| PRESS:COST | 0.444 | 2.594 | -0.876 | 1.082 | 0.663 | 0.805 | -0.384 | 0.766 |
| PRESS:PIPE | -0.954 | 1.809 | 0.787 | 0.863 | 0.086 | 0.907 | -3.161** | 1.555 |
| PRESS:RELIA | -1.637 | 1.121 | 0.461 | 1.196 | 2.717*** | 0.847 | 0.110 | 0.523 |
| QUAL:COST | 4.312 | 4.205 | -4.454** | 1.814 | 2.189*** | 0.614 | 0.011 | 0.482 |
| QUAL:PIPE | -3.775 | 4.629 | -3.252** | 1.507 | 2.925*** | 0.775 | 3.153** | 1.310 |
| QUAL:RELIA | -3.563 | 2.554 | -2.318 | 1.652 | -0.865 | 0.630 | -1.108 | 0.744 |
| QUAL:PRESS | -1.314 | 2.878 | -2.372* | 1.422 | 0.808* | 0.477 | 1.761** | 0.818 |
| **Variance parameter tau in GMX scale parameter** | | | | | | | | |
| TauScale | 1.336*** | 0.168 | 1.297*** | 0.248 | 0.800*** | 0.116 | 1.243*** | 0.242 |
| **Weighting parameter gamma in GMX model** | | | | | | | | |
| GammaMXL | 0.0 | 0.124 | 0.0 | 0.031 | 0.00 | 0.062 | 0.0 | 0.033 |
| **Sample Mean and Sample Std. Dev.** | | | | | | | | |
| Sigma(i) | 0.906 | 1.480 | 0.922 | 1.443 | 0.966 | 0.836 | 0.926 | 1.376 |
| **Standard deviations of parameter distributions** | | | | | | | | |
| sdCOST | 0.003 | 0.002 | 0.012** | 0.005 | 0.017*** | 0.003 | 0.011** | 0.004 |
| sdPIPE | 1.625 | 2.327 | 4.401*** | 1.622 | 3.004*** | 0.598 | 2.882*** | 0.326 |
| sdRELIABILITY | 4.571*** | 0.997 | 5.554** | 2.295 | 4.190*** | 0.770 | 3.431** | 1.421 |
| sdPRESSURE | 1.981 | 1.446 | 4.700** | 2.064 | 2.946*** | 0.737 | 5.134*** | 0.942 |
| sdQUALITY | 7.840*** | 2.780 | 8.197*** | 1.170 | 3.853*** | 0.711 | 4.160*** | 1.522 |

Note: ***, ** and * = significance at 1%, 5%, 10% level, respectively. Par Est. = parameter estimates. Std. Err = standard errors

The $ASC_{SQ}$ estimates for the first blocks of each sub-sample are both statistically significant at the 1% significance level. Positive and statistically significant $ASC_{SQ}$ estimates in the first blocks of the two sub-samples indicate the existence of SQ bias. These findings are consistent with revelations from Samuelson and Zeckhauser (1988) and several other previous studies that revealed that many respondents disproportionately choose the SQ option if offered their relevant SQ. Regarding the second blocks of each sub-sample, we expected the $ASC_{SQ}$ estimates to be statistically insignificant. However, contrary to our prior hypothesis, the $ASC_{SQ}$ estimates for the second blocks were also positive and statistically significant. This could be because most respondents chose neither the SQ option nor the hypothetical options, but rather the 'none' option, as revealed earlier in Figure 2. Such choices may be reflected by the positive and significant $ASC_{SQ}$.

As explained earlier, the aim of this study is not to show evidence of SQ bias, but to test whether utility functions differ across blocks in the given sub-samples. Therefore, the estimation results presented in Table 6 will be interpreted based on the sign, significance and magnitude of the random parameter coefficients that make up the utility functions. More precisely, the study compares the coefficients of the random parameter estimates in each stratum, and across the sub-samples. A comparison of these coefficients gives information on whether utility functions vary across blocks.

Positive attribute coefficients indicate household preference for changes in the attribute. For instance, the positive coefficient of PRESSURE in the suburban blocks indicate that households prefer changes in the water pressure. To be specific, a unit change in PRESSURE increases households' utility by about 5.23 units in suburbs block 1, and by 5.65 units in suburbs block 2. On the other hand, negative coefficients suggest that households do not prefer changes in the attribute. For example, the negative coefficients of PIPE in in the suburban blocks indicate that suburban households do not prefer changes in the way they access piped water services. More precisely, the PIPE results suggest that a unit change in access to piped water reduces utility by about 4.23 units in suburbs block 1, and 2.72 units in suburbs block 2.

The first step in our bid to examine the impact of SQ bias will test whether variations exist in the utility functions across blocks. Therefore, we compare utility functions in each sub-sample in terms of the signs and magnitudes of the coefficients. The sign of the attribute parameter shows the impact of an attribute to respondents' utility, while the magnitude of the coefficient shows the extent of impact each attribute has on utility. In the suburbs sub-sample, two variations are noted in the signs of COST and RELIABILITY across the two blocks. In the township sub-sample also, two variations are noted across blocks, in the signs of RELIABILITY and PRESSURE. Regarding the magnitudes of parameter estimates, no huge discrepancies are noted across blocks in either sub-sample. Magnitudes of coefficients are consistent across the blocks of each sub-sample.

Although the signs and magnitudes of parameter estimates are essential when examining utility functions, the statistical significance of the parameters is more important in determining preferences. Statistical significance shows the attributes that are important to households, as well as those that are not important. Therefore, a comparison of the statistical significance of the attribute parameter coefficients across the blocks of each sub-sample is essential. In the suburbs sub-sample, only the coefficients for PIPE are not consistent across the two blocks; the coefficient is insignificant in block 1, but significant at 1% in block 2. The rest of the coefficients are consistent in terms of statistical significance across the two suburban blocks. Notable variations are seen only in the level of significance where, for example, the significance level for COST is 1% in block 1 but 10% in block 2. Overall, there is consistency in the statistical significance of parameter estimates across the suburban blocks. Regarding statistical significance in the township sub-sample, coefficients for all the five attributes are consistent across blocks. Where estimates are statistically significant in the first block, they are also significant in the second block, and vice versa.

In addition to the five attributes modelled as random parameters in the utility functions, we also controlled for six selected socio-economic characteristics (AGE, EDUCATION, GENDER, INCOME, RACE and STATUS). We considered these variables because we hypothesise that they are essential in determining how individuals make choices. For example, elderly respondents are expected to make different choices to younger respondents. Equally, a respondent's level of education, income level, race and marital status are also expected to be key determinants of choice. The empirical results in Table 6 show that none of these socio-economic characteristics were significant determinants of respondents' choices in suburbs block 1. However, in the second block of the suburbs sub-sample, INCOME and RACE were important determinants of choice. In the township sub-sample, EDUCATION was an important determinant in block 1, while AGE and GENDER were important determinants in block 2.

### *8.3. MWTP estimates*

We also examined whether the different utility functions given in the different blocks would also yield the same welfare measures. To do this we estimated the households' MWTP for the given attributes. MWTP is a welfare measure that shows average estimates of what households are prepared to pay for or against changes in each attribute. Positive and significant estimates show the average amount that households are willing to pay, while negative and significant estimates show how much they are willing to accept as compensation. The MWTP estimates are presented in Table 7.

**Table 7:** Marginal willingness to pay estimates (in US Dollars)[7]

| | **Suburbs** | | | | **Townships** | | | |
|---|---|---|---|---|---|---|---|---|
| | Block 1 | | Block 2 | | Block 1 | | Block 2 | |
| | Estimate | Std. Err. | Estimate | Std. Err. | Estimate | Std. Err. | Estimate | Std. Err. |
| PIPE | 31.06 | 26.09 | -42.23*** | 14.06 | 1.46 | 1.71 | 1.10 | 1.22 |
| RELIABILITY | 26.21 | 24.11 | 18.06 | 14.23 | 3.22 | 3.26 | -0.01 | 3.91 |
| PRESSURE | -31.24* | 16.63 | 87.45*** | 24.91 | 2.36 | 3.79 | -3.28 | 5.08 |
| QUALITY | 74.82** | 32.67 | -172.12*** | 58.30 | -14.79*** | 2.63 | -18.26*** | 3.25 |
| **Wald Statistic** | **1.85** | | **0.96** | | **2.42** | | **2.41** | |
| **Prob. from Chi$^2$** | **0.000** | | **0.008** | | **0.000** | | **0.000** | |

Note: ***, ** and * = significance at 1%, 5%, 10% level, respectively. Std. Err are standard errors.

The MWTP estimates presented in Table 7 are consistent in terms of statistical significance in the township sub-sample, where parameter estimates for all attributes are insignificant except for the parameter estimates of the QUALITY attribute. The MWTP estimates for QUALITY are both negative and statistically significant at 1% significance level. The negative sign suggests that households are not willing to pay for any changes in the quality of the water they receive. More precisely, township households in block 1 are willing to accept $14.79 as compensation for changes in the quality of water, while in block 2 they are willing to accept $18.26 as compensation

[7] As at 24 October 2018, US$1 = ZAR14.30

for changes in the quality of water. In a nutshell, different SQs did not affect MWTP estimates across the blocks of the township sub-sample, as the estimates are consistent across the two blocks.

In the suburbs sub-sample, there are inconsistencies across the two blocks. The only attribute with consistent parameter estimates in terms of sign and significance is RELIABILITY, which is statistically insignificant across the two suburban blocks. The rest of the attributes recorded inconsistent estimates in terms of sign and/or significance. Firstly, the MWTP estimate for PIPE is positive and statistically insignificant in block 1, but positive with a statistical significance of 1% in block 2. Secondly, the MWTP estimate for PRESSURE is negative with a statistical significance of 10% in block 1, but positive with a statistical significance of 1% in block 2. Finally, although the MWTP estimates for the QUALITY attribute are both statistically significant, in block 1, households from the suburbs are willing to pay $74.82 for changes in the quality of their water; yet in block 2, they are willing to accept $172.12 as compensation if the water quality changes. Inconsistencies in the suburbs sub-sample suggest that SQs may affect the MWTP estimates.

## 8. Conclusion

This paper tests for the effects of reducing status quo bias considering a heterogeneous sample. We test this by introducing a partially relevant status quo aimed at reducing SQ bias in a choice experiment that elicits household preferences for water service packages in Durban, South Africa. To achieve this, we stratify our sample into two sub-samples (i.e. suburbs and townships). Each sub-sample is presented with two experiments, one containing a relevant SQ (block 1) and another containing a partially relevant SQ (block 2). Based on the hypothesis that introducing a partially relevant SQ reduces SQ bias, we test whether the likelihood of a participant choosing the SQ is driven by the relevance or partial relevance of the SQ option. Subsequently, we test whether this affects empirical results by comparing the significance, sign and absolute values of attribute parameters as well as MWTP estimates across the two blocks in each sub-sample. We use the GMXL and MXL models as estimation tools. However, we present empirical estimates from GMXL based on goodness-of-fit tests, which revealed that GMXL outperformed MXL.

The tests show that presenting each split sample with a partially relevant status quo reduces the status quo bias problem. Since this finding was consistent with our hypothesis, we proceeded to estimate the households' preferences for water service packages. Results from our tests revealed that parameter estimates across the two blocks of the township sub-sample were largely similar in terms of sign, statistical significance and the absolute value of the parameters' magnitude. Only COST and QUALITY emerged statistically significant in both blocks. These two attributes contained the same signs and had coefficients of the same magnitude in absolute terms. Similarities in the two blocks of the township sub-sample were also observed in the MWTP estimates. QUALITY was the only attribute with statistically significant MWTP estimates that also had the same sign and a similar coefficient magnitude across the two blocks.

In the suburban sub-sample, we found that all attributes except one reported the same statistical significance across the two blocks. The statistically significant parameters had the same signs, except for COST, which had a positive coefficient in block 1 and a negative coefficient in block 2. A positive coefficient in block 1 suggests that respondents preferred higher monthly water bills. Such a revelation is not consistent with either our prior expectations or the common findings in the literature, where the cost attribute generally has a negative coefficient (see Anand, 2001; Bhaduri and Kloos, 2013; Brouwer et al., 2015; Hensher et al., 2005). An analysis of the size of the coefficients showed no major differences across the two suburban blocks. We found that the attribute parameters were of the same magnitude, in absolute terms.

Estimation results in the suburban sub-sample imply that to a large extent, the relevance or partial relevance of the SQ did not affect the utility functions. However, the MWTP estimates in the two blocks of the suburban sub-sample reported disagreeing results in terms of sign and significance. Block 1 had two attributes that were statistically significant, while block 2 reported statistical significance on three attributes. Most importantly, we observed that all the statistically significant MWTP estimates had different signs across the two suburban blocks.

Overall, we argue that the inclusion of a partially relevant SQ reduced SQ bias, but did not affect estimates of attribute parameters, in both suburbs and townships. However, huge discrepancies were noted in the MWTP estimates of the suburban sub-sample. For future studies, we recommend they present choice experiments containing both relevant and partially relevant SQs to the same respondents. Our study used different respondents with similar socio-economic characteristics to answer the two questionnaires presented in each sub-sample. This was done to avoid fatigue and learning by the respondents. Secondly, we recommend against the inclusion of a ‘none’ option when conducting experiments such as ours. We included the ‘none’ option, in addition to the SQ option and the two experimentally designed hypothetical options. This proved to be problematic in block 2, because many respondents selected the ‘none’ option. We argue that the omission of the ‘none’ option as an opt-out choice would motivate respondents to make real trade-offs, by having to choose between the hypothetically designed options and the status quo.

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