Title:

Investigating users' preferences for Low Emission Buses: Experiences from Europe's largest hydrogen bus fleet

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1. Introduction

Public transport plays a vital role in mobilising people to their workplaces and leisure centres across urban settings. In the United Kingdom (UK), buses are the most common form of public transport (Department for Transport, 2018). The majority of buses are powered using diesel fuel, which emits different types of emissions when combusted. These emissions contribute to climate change and create pollution hotspots in city and town centres[1] (Potter, 2003). Given the diversity of effects, emissions from diesel fuel buses can be categorised into those having predominantly global (i.e. climate change) and local effects (i.e. increased health problems in communities). There is limited evidence of which of the two types of emission is valued more highly or whether individuals are willing to trade-off between them.

The introduction of Low Emission Buses (LEB) could reduce the amount of emissions generated from bus travel. LEBs are defined as a bus that "operates using efficient technology or alternative fuels rather than just a traditional diesel engine. They are defined by the UK Government as producing 15% less Well-to-Wheel[2] emissions compared with an equivalent Euro V standard diesel bus" (Low Carbon Vehicle Partnership, 2018). Existing LEBs in Europe are all part of small-scale pilot fleets, implemented in isolation from one another, typically without secured long-term financing. Two recurrent barriers to the introduction of new LEB fleets or the expansion of existing current ones are high upfront costs and uncertainty of whether bus users value reduced emissions.

This research presents the findings of a Discrete Choice Experiment (DCE) administered amongst bus users to examine their preferences for the different characteristics of bus travel, including different types of emissions. This DCE was administered in Aberdeen (Scotland), which is home to Europe's largest hydrogen bus fleet - the Aberdeen Hydrogen Bus Project (AHBP). The AHBP introduced 10 hydrogen fuel cell buses on two local routes that were previously serviced using diesel engine buses. The way in which the AHBP was introduced

[1] There is extensive evidence linking the pollutants from fossil fuel combustion to health problems amongst people who are exposed to the pollution (COMEAP, 2009; Gowers et al., 2014; Walton et al., 2015).
[2] Also known as a life-cycle analysis. This is the assessment of the environmental impact (i.e. emissions generated) of the fuel throughout its lifespan, including resource extraction, fuel production, delivery to vehicle and end use for bus operation.

created a natural experiment in which bus users differ in their experience using a zero emission bus. This allows us to test how bus users' direct experience affects their preferences and explore the role of experience and familiarity on individuals' stated preferences. In doing so, we contribute to the limited number of studies in this area (Cherchi and Hensher, 2015).

We find that Aberdeen bus users place a higher value in reductions of local pollutant emissions over those emissions that relate to global climate change. This questions the common practice in stated preference studies of framing emission attributes in terms of carbon or greenhouse gas emissions only. We also find evidence of the effect of direct experience in preference formation. Specifically, bus users who regularly use hydrogen buses display different preferences for the comfort inside the bus and emissions, compared to users who occasionally or never use hydrogen buses.

The outline for this paper as follows: first, we present an overview of previous stated preference studies that value emissions from road transport, and research on the role of experience in preferences for environmental goods. Second, we describe the DCE survey and data collection methods. Third, we present the results obtained across several model specifications in terms of the values for the different bus attributes. We test the role of experience on preferences by separating the sample according to the level of experience using a hydrogen bus. Fourthly, we discuss the policy implications of our results.

2. Literature Review

Stated preference methods, and more specifically DCEs, have been widely used to investigate preferences for reduced emissions in road transport. The majority of these studies have focused on private alternative fuel vehicles (AFV). These have presented respondents with a choice of vehicle types described in terms of attributes related to their travel needs (i.e. range, refuelling capability), vehicle performance and in some cases, policy incentives designed to increase uptake of AFVs. A summary of the ones relevant to this study is presented in this paper[3]. Some

[3] A table with a comprehensive review of the existing private vehicle studies is presented in the Appendix.

studies have included and valued a vehicle emissions attribute, while others have described the different technologies (battery-electric, petrol, etc.) as an attribute (or alternative specific label) and valued emissions implicitly through the associated technology and emissions (Adler et al., 2003; Axsen et al., 2015; Hackbarth and Madlener, 2013; Hidrue et al., 2011; Krause et al., 2016; Valeri and Danielis, 2015). For those studies that have included an emissions attribute, there is no consensus of how to present and describe this to respondents (Achtnicht et al., 2012; Beck et al., 2011; Brownstone et al., 1996; Caulfield et al., 2010; Higgins et al., 2017; Link et al., 2012; Mabit and Fosgerau, 2011; Maness and Cirillo, 2012; Tanaka et al., 2014; van Rijnsoever et al., 2013). Most studies describe emissions in terms of a generic pollution, while more recent studies present emissions in terms of carbon (or greenhouse gas related) emissions. No study has included two different types of emissions, meaning that emissions primarily related to local air quality or health issues have been largely ignored[4].

There are fewer studies about preferences for low emission bus transport. A number of DCE studies have examined buses as a modal choice, without consideration of environment-related attributes. For instance, DCEs have been used to develop Service Quality Indices (Eboli and Mazzulla, 2008; Hensher and Prioni, 2002; Hensher, 2015; Marcucci and Gatta, 2007; Román et al., 2014), examine improvements for a single route (Baidoo and Nyarko, 2015; Kumar et al., 2004; Lu et al., 2018; Swanson et al., 1997), elicit preferences for fare simplification (Hess et al., 2013), and compare bus travel with other transport modes (Alpizar and Carlsson, 2003; Axhausen et al., 2008; Bhat and Sardesai, 2006; Espino et al., 2007). A comprehensive list of all studies have included a bus alternative, including the attributes and levels used, can be found in the Appendix.

Four studies have investigated preferences for emission reduction in buses using the Contingent Valuation Method (CVM). O'Garra et al. (2007) investigated bus users' willingness to pay (WTP) to introduce hydrogen buses in Perth (Australia), Luxembourg, London and Berlin. They found users were willing to pay an extra €0.35, €0.33, €0.29 and €0.27 in higher fares for hydrogen buses. They also found non-users were willing to pay €24.2 and €15.67 in higher annual taxation for hydrogen buses in London and Perth respectively. Heo and Yoo (2013)

[4] Van Rijnsoever et al. (2013) is the only study that has included a "local emissions" attribute on its own. Moreover, their survey was not aimed at users, and was instead administered to public servants in Dutch local governments.

found households in Korea were willing to pay US$4.55 as an annual payment to fund the widespread introduction of hydrogen buses. They also found that respondents who knew about hydrogen buses had a higher WTP, but they did not consider respondents' experience of hydrogen buses. Bigerna and Polinori (2014) found residents of Perugia, Italy were willing to pay €0.31 higher bus fares to fund the large-scale introduction of hydrogen buses. Bigerna and Polinori framed the environmental benefit as less smog, which reduced damage to historical buildings in the city centre. Gupta (2016) found road vehicle passengers (including bus users) were willing to pay Rs581.50[5] in tax to mitigate carbon dioxide emissions from passenger transport. Gupta also found that respondents who had health problems were willing to pay more for reduced carbon emissions.

An underlying assumption of the economic theory on which all the previous studies are based is that individuals have well-defined preferences (Freeman III et al., 2014). This assumption may not hold in the context of environmental goods, with which respondents are often unfamiliar (Cummings et al., 1986; Gong and Aadland, 2011). Stated preference researchers make extensive efforts to provide sufficient information alongside the survey to enable individuals to form well-defined preferences (Arrow et al., 1993; Munro and Hanley, 2001). Moreover, the ways in which individual's gain familiarity with environmental goods and how this process is related to an individuals' direct experience has received little attention (Cherchi and Hensher, 2015). There is no consensus on the mechanisms with which familiarity is obtained (Czajkowski et al., 2014).

Familiarity can be acquired either endogenously from the amount of information or experience the individual has before any valuation exercise takes place, or be provided exogenously as information during the survey (Cameron and Englin, 1997; Mitchell and Carson, 2013). The extent to which one method can substitute the other remains relatively unexplored (Czajkowski et al., 2016). The effects of in-survey information provision, knowledge and direct experience of a good are often used interchangeably as proxies for familiarity in the stated preference literature (Cameron and Englin, 1997; LaRiviere et al., 2014; Needham et al., 2018). This leads to the assumption that providing in-survey information is sufficient for respondents to gain

[5] Approximately US $9.00

enough familiarity of the good in question (Carson and Louviere, 2011; Hoyos, 2010). Empirically testing whether this assumption is accurate is challenging.

The evidence of the sole effect of experience on respondents' WTP for environmental goods is mixed. Several studies across a range of environmental goods have found that respondents' direct experience of the good positively affected their WTP (Bohara et al., 2007; Breffle and Morey, 2000; Hanley et al., 2010; Kosenius and Ollikainen, 2013; Rambonilaza and Brahic, 2016; Tu and Abildtrup, 2016). Concurrently, studies have found that limited experience of a good has no effect on WTP (K. J. Boyle et al., 1993; Hensher and Battellino, 1992). Cameron and Englin (1997) described this as the need for the *crystallization* of experiences, implying that there is a threshold of experience needed for preferences to be affected. For example, Hanley et al. (2009) found evidence of this need for a certain minimal level of experience in a study looking at WTP for improved water quality amongst beach goers and residents of a coastal community. In the context of travel, Jensen et al. (2013) used a long panel survey to find that individual preferences changed after a 3-month experience with an electric car. Long panel stated preference studies are often logistically difficult to carry out and, in the case of Jensen et al.'s, prone to self-selection bias. The use of natural experiment like the AHBP can avoid these limitations.

3. Methods

Aberdeen is Scotland's third largest city. It has over 30 urban bus routes. Local bus users were surveyed across Aberdeen City bus stops between the months of October and December 2016 using Computer Aided Personal Interviews. Figure 1 shows the spatial distribution density of the sample[6]. Respondents were approached by trained interviewers at random while they were waiting for their bus. The survey consisted of four main sections. First, screening questions to determine the type of bus respondents typically used. The second section included four DCE choice tasks. The third section asked respondents' attitudes to the environment and local air quality, and the fourth section gathered socioeconomic data. The survey design was informed by a review of existing studies and an extensive qualitative research stage, which included focus

[6] Sample sites were chosen based on those used by previous council local bus satisfaction surveys.

group discussions, think-aloud interviews, and iterative rounds of pilot testing. Realism was an ongoing concern; thus, throughout the design process local bus users' involvement was sought to ensure the DCE tasks were relatable.

In the DCE, respondents were asked to choose between three unlabelled future bus services, described by seven attributes. The bus attributes and their levels were chosen following feedback of local users, both from the focus groups and the results of previous non-academic passenger satisfaction surveys[7]. Table 1 presents the attributes and levels used. The context used to describe the attributes was informed by local experiences to ensure the choice tasks were both meaningful to the average bus user and applicable to their real bus travel experience. Given the uncertainty surrounding the different types of emissions and stemming from the results of involving local users, global emissions were framed in terms of greenhouse gas (GHG) emissions and local emissions in terms of Nitrogen Oxides and Particulate Matter[8].

The choice tasks included in the DCE were obtained from a Bayesian D-efficient design, using priors from a pilot survey[9]. A heterogeneous reference dependent segmented design was used to create choice sets that were realistic for the different bus routes that exist in Aberdeen (Rose et al., 2008). In this design, the reference alternative described the respondent's current bus service. Respondents were assigned to one of four segments, based on the observed route frequency[10] and fuel type of their most used service. The attribute levels of the remaining alternatives were pivoted from the levels of each segment's reference alternative. Table 1 describes the pivoting of the attributes and levels for each segment. Once assigned to their respective segment, respondents were randomly assigned to one of five blocks of questions.

[7] For example, the decision to include driver friendliness was solely motivated from the qualitative research findings. Another example is the range of minutes used in the punctuality attribute and the decision to cap the upper fare level at £3.
[8] Both types of emissions were explained to the respondent during the survey. Findings from the qualitative stage suggested respondents engaged better with the *final good* concept (i.e. the consequence) of the different emissions, rather than the *intermediate good* (i.e. the emission name). For example, GHG emissions meant little to them, but they knew it caused global problems. Similarly for the local pollutants. As such, while the intermediate good was presented in the choice task, the final good of each type of emission was described prior to the choice task.
[9] The experimental design for this pilot survey was a D-efficient design, using zero as priors. Results from a multinomial model were used as priors for the main study.
[10] Frequency is typically measured in terms of service headway. A standard segmentation of bus service frequency is to divide them into high and low frequency buses (TfL, 2017). Boyle (2006) and Fattouche (2011) provide a detailed discussion of the convenience of this segmentation.

The use of an intercept survey at bus stops meant that we anticipated a high data attrition rate from respondents whose bus arrived and did not complete the entire survey. Therefore, we focussed on minimising the survey length and created reverse blocks of questions for each segment. These blocks displayed the choice tasks in reverse order from the original block, thus ensuring that in case a significant number of respondents dropped out during the DCE section there would not be a disproportionate representation of data from the first choice sets for each block within each segment[11]. The survey was optimised so it took, on average, eight minutes to complete up to the last choice task and ten minutes to the end[12].

The choice data was analysed using multinomial (MNL) and mixed logit (MXL) models (Ben-Akiva et al., 1985; McFadden, 1974). Under the choice model framework, the utility individual *n* assigns to bus service *i* in choice task *s* is given by the sum of a systematic and unobserved random component, defined as:

$$U_{nis} = \beta_n' x_{nis} + \varepsilon_{ni} \ ,$$

where *x* is a vector of the bus service characteristics and is a vector of unknown parameters to be estimated. In a MXL model, these parameters are allowed to vary between respondents according to prescribed distributions. The error component, ε_{ni} is assumed to be independently and identically distributed extreme value type I and independent of β_n and $x_{nis.}$ Under these assumptions, the probability that an individual *n* chooses bus service *i* can be written as the logit probability (Train, 2009):

$$L_{ni} = \frac{\exp(\beta_n x_{ni})}{\sum_{j=1}^{J} \exp(\beta_n x_{nj})}$$

Since β_n and ε_{ni} are unknown, the solution requires integrating over all the possible values of β_n weighted by the selected densities. The unconditional probability of the observed sequence of choices for a given choice set *s* is given by:

$$P_{nis}(\theta) = \int L_{nis} f(\beta|\theta) d\beta$$

A simulated maximum likelihood estimator is used to estimate the probabilities. For each coefficient specified as random, 1000 Halton draws from the distribution are taken. The mean

[11] Software limitations did not allow for question randomisation within each block.
[12] The average waiting time for a high frequency bus in Aberdeen.

logits from the logit calculation of each draw approximates the choice probability. The systematic component of the utility is assumed linear additive, specified as:

$$V_{nis} = \beta_0 + X_1\beta_1 + \cdots + X_t\beta_{tn} \ ,$$

where β_0 is an Alternative Specific Constant (ASC), reflecting the average effect of the unobserved bus characteristics of choosing the current service relative to the others. β_1 to β_T are the parameters for each of the attributes listed in Table 1. Marginal WTP for a unit change in an attribute level is calculated as the ratio of the partial derivatives of indirect utility function with respect to attribute *t*, and that with respect of the fare:

$$WTP = \frac{\frac{\partial V_{nis}}{\partial X_t}}{-\frac{\partial V_{nis}}{\partial X_{fare}}}$$

We use different assumptions for the parameter distributions are used to test the validity of the welfare estimates presented in the results section[13] (Hole, 2008; Hole and Kolstad, 2012). When calculating WTP, there are implications when assuming a normally distributed parameter for the fare attribute. First, the use of a normal distribution assumes a proportion of the respondents prefer higher fares, which is behaviourally implausible. Second, the ratio of two normally distributed coefficients does not have defined moments, which is an issue for the calculation of WTP. The use of lognormal distribution can help resolve these issues, although this comes at the expense of skewing the results. Random parameters in models N1 and N2 follow a normal distribution, while LN1 and LN2 have lognormal ones. Fare is fixed in N1 and LN1 and random in N2 and LN2.

We present a discussion of the suitability of each model specification for the pooled sample, assessing fit in terms of the log likelihood and Akaike Information Criterion, and choose the best-suited specification to explore whether varying levels of experience using a hydrogen bus has an effect on respondents' preferences. For this, we divide the sample according to the respondents' experience of using a hydrogen bus into three groups: frequent, occasional and never hydrogen users. We assume users whose regular service is a hydrogen one are *frequent* hydrogen users. Those whose current service was diesel, but have used hydrogen buses are

[13] All attributes are assumed random except for the emission interactions and ASC to ease interpretation. While we acknowledge this may have behavioural implications, we decided to focus on exploring and highlighting the heterogeneity of the time-based attributes (i.e. frequency and punctuality), emissions and fare.

occasional users. Finally, respondents who have never used a hydrogen are *never* users[14]. A dummy variable for each type of user was created and we estimate separate MXL models for each type. We compare the preferences across the different levels of experience by testing for variations in users' marginal WTP for the bus attributes. It is worth noticing that testing for preference differences using this separation of the sample assumes groups are the same. We test for this using gender (interviewer-collected at the start of the survey) and the sociodemographic characteristics of the different groups collected after the choice tasks.

4. Results

Responses from 338 users who completed at least one of the choice task were obtained and used for analysis. In terms of completion rates, 322 (95%) respondents completed all the choice tasks and 233 (69%) completed the entire survey. Most dropouts (97%) occurred because the respondents' bus arrived. We tested for differences across respondents in terms of three screening questions[15] and found no statistically significant difference between respondents who completed the entire survey and those who did not, suggesting data attrition was at random. Sociodemographic and travel behaviour characteristics obtained in Section 1 of the survey are described and compared to previous local bus satisfaction surveys in Table 2. Additional sociodemographic characteristics collected for the proportion of respondents who finished the survey are described in Table 3.

The DCE results are presented in Tables 4 and 5. Table 4 presents the results of the MNL and four MXL models as described in section 3. Table 5 presents the mean, median and standard deviations of the coefficients for the MXL models with log normal distributions, calculated using the delta method (Greene, 2003; Train, 2009). The DCE results are robust to model specification. Mean and median parameter estimates are consistent across the five models. On average, bus users prefer buses that are cheaper, more frequent, more punctual, and with reduced emissions. Bus users also seem to prefer less friendly drivers, which is counterintuitive. Comfort is not statistically significant, which suggests, on average, this attribute is not valued

[14] Although hydrogen buses were mainly used in the city two routes, they were sometimes used in other routes, facilitating frequent diesel users to experience them occasionally.
[15] Overall bus satisfaction, assessment of how friendly the driver is and perception of air quality in Aberdeen.

by bus users. There is evidence of significant preference heterogeneity for the frequency and emissions in all models, and for fare in models N2 and LN2. The MXL models in which fare is specified as a random parameter have better fit than those on which it is fixed. To explore further the appropriateness of fixing the fare attribute, the mean and median WTP for each model are shown in Tables 6 and 7.

The mean WTP for the frequency and punctuality attributes are consistent across model specifications. The choice of distribution affects the estimated WTP for GHG emissions. The mean values are significantly higher when lognormal distributions are assumed. The difference between median and mean WTP values for GHG reductions suggests the values are skewed in the lognormal distribution. To explore this, the kernel densities of the individual WTP estimates are presented in Figures 2 to 4. Figure 3 confirms the skewness of the distribution in models LN1 and LN2. This skewness is likely a direct consequence of the lognormal distribution assumption, meaning that median WTP values may be the more appropriate measure for this type of distribution. Figure 4 shows that WTP for local pollutants is skewed when assumed lognormal, albeit to a lesser extent than WTP for GHG. Across all specifications, WTP values[16] for local pollutant emission reductions are higher than that of GHG emissions. Determining which specification is best suited is not straightforward. WTP estimates are robust to model specification. Across the two distribution types, the model that has a random fare coefficient provides the best fit, with Model N2 providing the best fit overall. This specification however assumes a normally distributed fare coefficient, which limits the estimation of WTP. Models N1 and LN2 have similar fit, but mean WTP estimates from LN2 are highly skewed; therefore, our preferred model is N1[17].

The sociodemographic characteristics of the split sample groups according to experience are compared in Table 8. The results of using the model specification of N1 for each of the three groups described in the methods section are reported in Table 9. A likelihood-ratio test confirms the model that relaxes the assumption of equal preferences across the groups has statistically significant better fit than the restricted model in Table 4 (LR test - $\chi 2$ (30) = 88.33, $p<0.000$). The WTP values estimated from the results in Table 9 are reported in Table 10. The majority

[16] Mean for the normal distributions, and median for the lognormal distributions.
[17] Additional specifications were also estimated included using willingness to space to add robustness to the WTP estimates from model N1. Results are presented in the Appendix.

of parameters estimates across the three groups are consistent with the pooled model N1 in Table 4: users prefer services that are cheaper, more frequent and more punctual. However, experienced hydrogen bus users also prefer a comfortable service and are willing to pay 45 pence for an increase in comfort inside the bus. Furthermore, never and occasional hydrogen users do not have a statistically significant preference for reduced GHG emissions. Frequent hydrogen bus users are willing to pay 37 pence for a 50% reduction in GHG emissions, while the WTP of never or occasional hydrogen users is not statistically significantly different from zero.

Table 8 confirms there are differences in gender, age and employment of frequent hydrogen users and regular diesel users. These differences would be a problem if they were associated with preferences. We ran interaction models for each and found a significant result only for females caring more about comfort[18]. Given the characteristics of the split sample, the finding of added comfort in the frequent hydrogen group may be stronger if there was gender balance across the different groups. This difference in emissions preferences is further confirmed with the kernel density plots of the distribution of the individual WTP estimates presented in Figures 5 and 6. A substantial proportion of the distribution for reduced GHG emissions amongst never and occasional hydrogen users lies in the negative domain. Conversely, for the frequent hydrogen users this distribution is less spread and mainly in the positive domain. In terms of local pollutants, while all users value reduced emission, unobserved heterogeneity is lower among experienced hydrogen bus users compared to never and occasional ones. For both types of emissions, never hydrogen users exhibit significant heterogeneity in their preferences.

5. Discussion

Sociodemographic characteristics of the pooled sample are in line with what previous surveys have found, albeit there are differences in the gender and service satisfaction results. It is difficult to assess the *real* composition of the Aberdeen bus user sample, as results from satisfaction surveys tend to change every year. Results show Aberdeen users' preferences for characteristics related to the instrumental value of travel were as expected and consistent with

[18] Results available from the authors at request.

previous studies: bus users prefer cheaper buses that get them to their destination faster and more reliably. We found a value of time[19] (VOT) for the pooled sample of users that ranged between 10 and 15 pence per minute, or £6 and £9 per hour (Hensher, 2010). These values are comparable to the benchmark of £4.52 and £9.95 from the UK Department for Transport[20]. Hess et al. (2013) estimated a higher average value for bus trips of £14.18 for England, although they found it differed significantly across cities. As a further validity test, the VOT from the proportion of the sample who were concession holders or non-paying users (26% of the sample) was compared to that of paying users and found not to be statistically significant different (p=0.958), thus providing confidence that the results are in line with expectation. A finding that was counterintuitive was the fact users preferred less friendly drivers. A possible explanation would be an aversion towards talkative drivers who may delay the service. Respondents valued reduced emissions from their bus service. On average, the mean WTP is £1.46 in extra fare for a bus service that reduces 100% of emissions from a diesel bus. As a comparison, O'Garra et al. (2007) estimated a WTP of between €0.27 and €0.35 in extra fare. Bigerna and Polinori (2014) found a WTP of €0.35 or 20% extra of the ticket (versus 63% in this study). It is difficult to make a direct comparison between studies, as O'Garra et al. and Bigerna and Polinori both used CVM and valued a bus package rather than the emissions of the bus.

The fact bus users were, on average, willing to pay more for improved local air quality is consistent with a wide range of literature that has found individuals value reduction in the health risks associated with air pollution (Hammitt and Zhou, 2006; Leighl et al., 2006; Navrud, 2001; Saari et al., 2015). This is however, the first study that has made respondents face a decision that required them to trade-off emissions with mainly global and local effects[21]. The findings obtained add to the evidence that climate change is typically considered an abstract concept by most people, with consequences that are perceived both geographically and temporally distant (Bickerstaff et al., 2006; Leiserowitz, 2005; Lorenzoni et al., 2007; Moser and Dilling, 2004; Wolf and Moser, 2011). On the other hand, local consequences are more tangible to perceive, with solutions that are likely more clear-cut to implement (Bickerstaff and Walker, 2003;

[19] TfL (2016) defines VOT as the value of waiting an additional minute for a bus (i.e. headway changes).
[20] £4.52 is for non-commuting trips and £9.95 for commuting trips for "non-working travel" trips, which accounts for the majority of travel in the UK. These values are for all transport modes and not specific to bus travel only (Department for Transport, 2017)
[21] We are aware that climate change emissions have in fact local consequences. However, past studies have suggested individuals often associate climate change with global effects and not necessarily associate them with how it would affect their environment locally (Bickerstaff et al., 2006; DEFRA, 2007; Leiserowitz, 2005; Leiserowitz, 2007).

Dresner et al., 2007; Smallbone, 2012; Smallbone, 2010). Future stated preference studies focused on emission reductions should either include more than one type of emission, or alternatively include the most relevant emission type. Provided the research question allows it, studies ought to describe emissions in terms of those which consequences feel more direct to the respondent (such as local air quality or health risks), instead of distantly perceived climate change ones. From a policy perspective, ongoing and future emission-reducing projects would benefit from communicating their benefits to the public in terms of a local context, rather than only climate change ones.

The level of experience using a hydrogen bus was found to have an effect in the preferences for the two most salient differences between hydrogen and diesel buses: emissions and comfort. Both, frequent and occasional, hydrogen users exhibit less preference heterogeneity for the emission attribute that was deemed most important to all users (i.e. local pollutants) compared to never users. At the same time, experienced hydrogen users were the only group who exhibited a preference for increased comfort. This result is consistent with Cameron and Englin's *crystallization* concept, suggesting a threshold of experience is needed for it to have an effect on valuations. This would explain why occasional hydrogen users did not value added comfort. In the context of low emission travel, results are in line with previous studies that have found users tend to exhibit different attitudes (Graham-Rowe et al., 2012; Schmalfuss et al., 2015; Skippon et al., 2016) and preferences towards electric vehicles after using one (Jensen et al., 2013). These studies however, have relied on samples that have self-selected and presumably had a prior interest or affinity towards electric vehicles. Our study overcomes this limitation and shows that increased experience can be a driver of preference change amongst *neutral* users. Whilst there may be unobserved characteristics that may be also adding to this effect, the fact we find differences for the two distinct features that differ between buses suggests that experience on its own is at least partly responsible for this. Familiarity is a complex concept; moreover, this complexity should not warrant its polysemantic use across the stated preference literature. In this regard, our paper adds to the growing empirical literature that aims to disentangle effect of direct experience from that of information provision and knowledge.

Our results have three main limitations. First, the experimental design means that frequent hydrogen users were asked for willingness to accept (WTA) for more emissions and diesel users for WTP for reduced emissions. There is empirical evidence that WTP and WTA values differ (Horowitz and McConnell, 2002). This disparity cannot explain our results. We find differences across groups in terms of WTP for comfort, and we find differences in the valuation (both WTP and WTA) of both types of emissions across the groups. Second, using a pivoted design to ensure that choice tasks were meaningful to respondents limited the number of attributes and levels that we could include in the DCE design. Because we faced a constraint on how many bus users we would be able to sample, we included only three levels per segment for the quantitative attributes (fare, frequency, punctuality and emissions). In terms of the fare, the 70p deviation between levels may have been too large. The £3 fare alternative was chosen 12% of the time, thus the analysis could have been enhanced from using an intermediate level between £2.30 and £3. Furthermore, we could not match our emission reduction levels to existing LEB criteria[22]. Future studies would benefit from the inclusion of more levels that correspond to existing benchmarks, albeit they should still rely on qualitative research and piloting to ensure respondents find these meaningful and easy to understand. The use of labelled alternatives to explore specific low emission policy objectives could also be helpful.

Third, the presentation of some of the attributes and levels was very simplified. In the case of the emissions, given the scarce guidance on how to frame emissions in stated preference literature, we informed ours from the qualitative research. We found pollutant quantitates were an abstract concept to respondents, which led us to use easily interpretable percentage reduction levels. Our description of the driver friendliness attribute was vague, which may have contributed to our counterintuitive finding. Driver friendliness is not often included in DCE studies of bus travel. Furthermore, there is little guidance on how to frame this. As an example, Hensher et al. (2003) used a “Driver attitude” attribute with levels: “Very friendly”, “Friendly enough” and “Generally unfriendly” [23]. We decided to include this attribute based on our preliminary qualitative research findings, which suggested Aberdeen users found driver friendliness to be important for their bus experience. Moreover, it is challenging to develop an objective measure of driver friendliness since this can mean different things to different people.

[22] That is currently 15% GHG reductions for Low Emission Buses or 30% for Ultra Low Emission Buses (Low Carbon Vehicle Partnership, 2018).
[23] Other examples of how this attribute has been framed in the past bus DCE studies are included in the Appendix.

This links to the general challenge within the design of using attributes that may not be directly relevant to the main research questions but appear important to respondents a priori. For example, punctuality was included in the design as, when we prompted an on-time level for punctuality, participants found it unrealistic. We therefore decided to use real levels of punctuality in Aberdeen, estimating an average punctuality of around within 4 minutes the scheduled time (which was the base level). While it could be argued that punctuality is typically beyond the operators control and depends on exogenous factors (i.e. traffic, weather, etc.), we included this as an attribute to make the choice task more realistic to the respondents. The only other time based attribute was frequency – when prompted about it on the choice task, respondents factored in the likely delays, confounding frequency with punctuality. We felt the best strategy was to try to disentangle both time-based attributes and include them as separate attributes. As with driver friendliness and comfort, previous DCEs have used punctuality as part of their attribute array.

The decision to include these types of attributes is part of the trade-offs involved to design a DCE that is realistic and maintains engagement with users. An alternative strategy would be to display these as one level attributes as part of the array of characteristics, without it being part of the experimental design and analysis. Whether it is used for analysis or not, these attributes should be explicitly explained to the respondent. Follow up questions to gauge the respondents' understanding of any vague and abstract attributes could add validity of the results, provided there is no constraint in survey completion time that could result in lower sample sizes.

6. Conclusion

This paper has provided insight into bus users' preferences for Low Emission Buses. Findings suggest respondents place a higher value on reductions of local emissions over global emissions. Stated preference studies should reconsider their standard practice of framing emissions in terms of greenhouse gases or carbon only. At the same time, our findings suggest benefits from emission-reducing projects should be communicated in terms of local benefits to the wider public. This research used a natural experiment to provide empirical evidence of the effect of experience in preferences and add to the growing body of evidence that seeks to gain better understanding how familiarity is obtained and how it can affect preferences. We find more experienced hydrogen bus users elicited a positive value for comfort inside the bus and differences in their preferences for emission reductions, when compared to users with less experience. These differences seems to be driven in part by the direct experience of using a hydrogen bus regularly. In the context of ongoing low emission projects, preference elicitation in a static context will result in estimates that do not reflect the dynamic nature of valuations from people experiencing them and becoming more familiar with their benefits and costs. Further, the process of acquiring familiarity of a good remains complex. There is a need for more research on the mechanisms with which familiarity is obtained and how we can disentangle the effect of in-survey provision and direct experience.

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Tables and Figures:

Table 1. DCE attributes, levels, pivoting and variables.

	Description	Pivoting	Segments			
			Diesel Bus		Hydrogen Bus	
			High Frequency	Low Frequency	High Frequency	Low Frequency
Attributes						
Frequency	How frequent the bus is (mins)	Reference ± 5 mins	5, **10**, 15	10, **15**, 20	10, **15**, 20	15, **20**, 25
Comfort	The level of comfort the bus has. (Baseline: same comfort as now)	-	**Same comfort**, More comfortable			
Driver Friendliness	How friendly the bus driver is. (Baseline: same friendliness as now)	-	**Same friendliness**, More friendly			
Punctuality	How punctual the service is - within how many minutes from scheduled time the bus will come (mins)	-	1, **4**, 7			
Greenhouse Gas (GHG) emissions	The amount of GHG emissions compared to a standard diesel bus.	Reference ± 50%, 100%	**ZERO**, 50%, 100%		ZERO, 50%, **100%**	
Nitrogen Oxides and Particulate Matter (PMs and NOx) emissions	The amount of PMs and NOx (local pollutant) emissions compared to a standard diesel bus.	Reference ± 50%, 100%	**ZERO**, 50%, 100%		ZERO, 50%, **100%**	
Fare	The fare for a single trip (£)	-	1.60, **2.30**, 3.00			
Variables						
ASC	Alternative Specific Constant of choosing current service.	-	-	-	-	-
Emissions Interaction (GHGxPMsNOx)	Interaction between both types of emissions	-	-	-	-	-

Levels in bold are the reference levels for each segment.

Table 2. Socio-demographics compared to 2016 Aberdeen City Bus Passenger Satisfaction Survey and 2017 Bus Passenger Survey.

	Survey Results	Aberdeen City Bus Passenger Satisfaction Survey 2016	2017 Bus Passenger Survey in Scotland (First Aberdeen)
Gender			
Male	46.5%	32.2%	N/A
Female	53.5%	67.8%	N/A
Bus Service Satisfaction			
Very satisfied	11.2%	33.0%	39.0%
Fairly satisfied	44.4%	44.4%	48.0%
Neither	28.1%	12.8%	9.0%
Fairly dissatisfied	13.0%	5.4%	4.0%
Very dissatisfied	3.3%	4.4%	0.0%
Don´t know	0.0%	0.0%	-
Bus service use			
Every day	34.0%	46.4%	N/A
2-3 times a day	42.6%	39.0%	N/A
About once a week	16.3%	10.2%	N/A
About monthly	3.6%	3.0%	N/A
Hardly ever	3.5%	1.4%	N/A
Don´t know	0.0%	0.0%	-

Note: The Bus Passenger Survey only reports users of First Bus Company (and not Stagecoach users) in Aberdeen. There were no statistics detailing gender or frequency of use in the Bus Passenger Survey in Scotland. Sample size for this survey = 338.

Table 3. Additional sociodemographic results collected after the choice task

		Survey Responses	Aberdeen City Bus Passenger Satisfaction Survey 2016
Age			
16-25 years old	36	14.7%	26.6%
26-35 years old	47	19.2%	17.4%
36-45 years old	53	21.6%	11.4%
46-59 years old	46	18.8%	8.8%
60+ years old	61	24.9%	35.4%
Refused	2	0.8%	0.0%
Sample Size	*245*		
Highest Education Level Obtained			
Lower secondary school qualification	49	20.0%	-
Upper secondary school qualification	81	33.1%	-
University or college qualification below a degree	79	32.2%	-
University or college degree	36	14.7%	-
Sample Size	*245*		
Employment			
Full-time employment	90	37.2%	-
Part-time employment	58	24.0%	-
Unemployed	3	1.2%	-
Student	38	15.7%	-
Retired	60	24.8%	-
Other (Unspecified)	4	1.7%	-
Sample Size	*242*		

Table 4. Results from the Multinomial Logit and Mixed Logit Models (Number of Halton draws in parenthesis).

	MNL	Model N1 (1000)	Model N2 (1000)	Model LN1 (1000)	Model LN2 (1000)
	Coefficient *(Standard Error)*	Coefficient *(Standard Error)*	Coefficient *(Standard Error)*	Coefficient *(Standard Error)*	Coefficient *(Standard Error)*
ASC (Choose current service)	0.149	0.184	0.295*	0.281**	0.373**
	(0.106)	*(0.143)*	*(0.159)*	*(0.132)*	*(0.143)*
Frequency (increase of 1 minute between services)	-0.146***	-0.193***	-0.209***	-1.830***	-1.743***
	(0.011)	*(0.018)*	*(0.020)*	*(0.110)*	*(0.108)*
More comfort inside bus (Base: same comfort as now)	0.139	0.116	0.147	-2.823*	-2.321*
	(0.077)	*(0.098)*	*(0.105)*	*(1.399)*	*(1.272)*
Friendlier driver (Base: same friendliness as now)	-0.182**	-0.205**	-0.181*	-1.713*	-1.786*
	(0.077)	*(0.099)*	*(0.107)*	*(0.782)*	*(0.696)*
Punctuality (decrease of 1 minute in tolerance from schedule)	0.133***	0.184***	0.198***	-1.770***	-1.726***
	(0.017)	*(0.023)*	*(0.025)*	*(0.124)*	*(0.127)*
GHG (reduction of 10% from emissions of a diesel bus)	0.068***	0.084***	0.088***	-3.384***	-3.351***
	(0.009)	*(0.016)*	*(0.017)*	*(0.371)*	*(0.386)*
PMs and NOx emissions (reduction of 10% from emissions of a diesel bus)	0.117***	0.146***	0.155***	-2.202***	-2.175***
	(0.009)	*(0.014)*	*(0.016)*	*(0.134)*	*(0.134)*
Fare (increase in £)	-1.172***	-1.561***	-1.710***	1.502***	0.351***
	(0.077)	*(0.120)*	*(0.148)*	*(0.106)*	*(0.092)*
Interaction Emissions (GHG*PMsNOx)	0.185***	0.252***	0.252***	0.228***	0.225***
	(0.051)	*(0.066)*	*(0.066)*	*(0.064)*	*(0.068)*
Standard Deviations					
Frequency		0.124***	0.121***	0.632***	0.553***
		(0.025)	*(0.027)*	*(0.137)*	*(0.139)*
Comfort		0.284	0.310	1.164	0.885
		(0.345)	*(0.357)*	*(0.695)*	*(1.089)*
Driver Friendliness		0.148	0.143	0.280	0.114
		(0.644)	*(0.618)*	*(2.143)*	*(3.037)*
Punctuality		0.011	0.008	0.012	0.036
		(0.138)	*(0.219)*	*(0.414)*	*(0.467)*
GHG		0.171***	0.183***	1.164***	-1.651***
		(0.020)	*(0.022)*	*(0.310)*	*(0.348)*
PMs and NOx emissions (local pollutants)		0.094***	0.107***	0.734***	0.755***
		(0.22)	*(0.023)*	*(0.167)*	*(0.158)*
Fare			0.911***		0.527***
			(0.186)		*(0.121)*
Log likelihood	-1219.03	-1179.41	-1173.73	-1187.49	-1183.53
Observations	3951	3951	3951	3951	3951
AIC	2460.07	2388.83	2379.46	2404.98	2399.07
BIC	2529.17	2483.05	2479.97	2499.21	2499.58

*** p<0.001, **p<0.05, *p<0.1. Values in Models LN1 and LN2 are the natural log of the parameter estimate.

Table 5. Mean, median and standard deviation from Models LN1 and LN2.

	Model LN1			Model LN2		
	Mean	Median	S.D.	Mean	Median	S.D.
	(S.E.)	*(S.E.)*	*(S.E.)*	*(S.E.)*	*(S.E.)*	*(S.E.)*
Frequency (increase of 1 minute between services)	-0.196***	-0.160***	0.137***	-0.204***	0.175***	0.122**
	(0.018)	*(0.017)*	*(0.042)*	*(0.019)*	*(0.018)*	*(0.039)*
More comfort inside bus (Base: same comfort as now)	0.117	0.059	0.198	0.145	0.098	0.158
	(0.093)	*(0.083)*	*(0.192)*	*(0.099)*	*(0.125)*	*(0.284)*
Friendlier driver (Base: same friendliness as now)	-0.187*	-1.800	0.053	-0.168*	-0.168	0.019
	(0.095)	*(0.141)*	*(0.427)*	*(0.101)*	*(0.116)*	*(0.517)*
Punctuality (decrease of 1 minute in tolerance from schedule)	0.170***	0.170***	0.002	0.179***	0.178***	0.006
	(0.021)	*(0.021)*	*(0.070)*	*(0.023)*	*(0.023)*	*(0.083)*
GHG (reduction of 10% from emissions of a diesel bus)	0.130***	0.033**	0.483	0.137**	0.035**	0.517
	(0.035)	*(0.013)*	*(0.367)*	*(0.043)*	*(0.013)*	*(0.456)*
PMs and NOx emissions (reduction of 10% from emissions of a diesel bus)	0.144***	0.111***	0.122**	0.151***	0.113***	0.132**
	(0.015)	*(0.015)*	*(0.042)*	*(0.016)*	*(0.015)*	*(0.043)*
Fare (increase in £)	-	-	-	-1.631***	-1.200***	0.922***
				(0.139)	*(0.131)*	*(0.275)*

Table 6. Mean willingness to pay estimates.

	MNL		Model N1		Model LN1		Model LN2	
	Mean	CI	Mean	CI	Mean	CI	Mean	CI
	(SE)		(SE)		(SE)		(SE)	
Frequency	0.124	0.105	0.124	0.103	0.130	0.107	0.125	0.102
	(0.010)	0.145	(0.011)	0.145	(0.012)	0.154	(0.012)	0.148
Punctuality	0.114	0.085	0.118	0.092	0.113	0.087	0.109	0.082
	(0.015)	0.143	(0.014)	0.145	(0.013)	0.140	(0.013)	0.136
GHG	0.058	0.043	0.053	0.035	0.086	0.042	0.084	0.032
	(0.007)	0.073	(0.010)	0.072	(0.022)	0.131	(0.026)	0.135
PMs and NOx emissions (local pollutants)	0.100	0.083	0.093	0.076	0.096	0.077	0.093	0.072
	(0.009)	0.117	(0.009)	0.110	(0.010)	0.116	(0.010)	0.112

CI = 95% Confidence Intervals

Table 7. Median willingness to pay estimates.

	MNL		Model N1		Model LN1		Model LN2	
	Median (SE)	CI	Median (SE)	CI	Median (SE)	CI	Median (SE)	CI
Frequency	0.124	0.105	0.124	0.103	0.107	0.084	0.123	0.093
	(0.010)	0.145	(0.011)	0.145	(0.011)	0.130	(0.015)	0.153
Punctuality	0.114	0.085	0.118	0.092	0.113	0.087	0.125	0.093
	(0.015)	0.143	(0.014)	0.145	(0.013)	0.140	(0.016)	0.158
GHG	0.058	0.043	0.053	0.035	0.023	0.006	0.025	0.005
	(0.007)	0.073	(0.010)	0.072	0.009	0.039	(0.009)	0.043
PMs and NOx emissions (local pollutants)	0.100	0.083	0.093	0.076	0.074	0.053	0.079	0.056
	(0.009)	0.117	(0.009)	0.110	(0.010)	0.094	(0.012)	0.103

CI = 95% Confidence Intervals

Table 8. Descriptive statistics of the split sample according to bus type.

	Diesel Users	Hydrogen Users	All Users	*p*-value
Gender				
Male	41.7%	60.5%	46.5%	<0.01
Female	58.3%	39.5%	53.5%	<0.01
Sample Size	*252*	*86*	*338*	
Age				
16-25 years old	15.60%	12.30%	14.70%	0.52
26-35 years old	17.20%	24.60%	19.20%	0.19
36-45 years old	20.60%	24.60%	21.60%	0.50
46-59 years old	13.90%	32.30%	18.80%	<0.01
60+ years old	31.70%	6.20%	24.90%	<0.01
Refused	1.10%	0.00%	0.80%	0.39
Sample Size	*180*	*65*	*245*	
Highest Education Level Obtained				
Lower secondary school qualification	23.00%	12.30%	20.00%	0.06
Upper secondary school qualification	37.00%	23.00%	33.10%	0.04
University or college qualification below a degree	27.50%	46.10%	32.20%	<0.01
University or college degree	13.50%	18.40%	14.70%	0.18
Sample Size	*180*	*65*	*245*	
Employment				
Full-time employment	33.10%	51.60%	37.20%	<0.01
Part-time employment	23.60%	25.00%	24.00%	0.82
Unemployed	1.70%	0.00%	1.20%	0.29
Student	16.90%	14.10%	15.70%	0.60
Retired	29.80%	10.90%	24.80%	<0.01
Other (Unspecified)	1.10%	3.10%	1.70%	0.27
Sample Size	*178*	*64*	*242*	

Note. *Never* and *occasional* hydrogen users are categorised here as Diesel Users.

Table 9. Results separating respondents by level of experience using a hydrogen bus.

	Never H2 Users	Occasional H2 Users	Frequent H2 Users
	Coefficient	Coefficient	Coefficient
	(S.E.)	*(S.E.)*	*(S.E.)*
ASC (Choose current service)	-0.672**	-0.693*	0.846
	(0.282)	*(0.335)*	*(0.550)*
Frequency (increase of 1 minute between services)	-1.110***	-0.111***	-0.365***
	(0.028)	*(0.030)*	*(0.052)*
More comfort inside bus (Base: same comfort as now)	0.033	-0.095	1.045***
	(0.151)	*(0.159)*	*(0.308)*
Friendlier driver (Base: same friendliness as now)	-0.348**	-0.457**	0.425
	(0.148)	*(0.163)*	*(0.314)*
Punctuality (decrease of 1 minute in tolerance from schedule)	0.124***	0.140***	0.202**
	(0.037)	*(0.042)*	*(0.068)*
GHG (reduction of 10% from emissions of a diesel bus)	-0.007	0.009	0.174***
	(0.031)	*(0.037)*	*(0.045)*
PMs and NOx emissions (reduction of 10% from emissions of a diesel bus)	0.063**	0.115***	0.231***
	(0.027)	*(0.030)*	*(0.049)*
Fare (increase in £)	-1.064***	-1.341***	-2.275***
	(0.172)	*(0.223)*	*(0.325)*
Interaction Emissions (GHG*PMsNOx)	0.252**	0.134	0.280
	(0.099)	*(0.107)*	*(0.233)*
Standard Deviations			
Frequency	0.145***	0.086*	0.001
	(0.036)	*(0.048)*	*(0.069)*
Comfort	0.501	0.122	0.091
	(0.359)	*(0.985)*	*(0.784)*
Driver Friendliness	0.068	0.096	0.440
	(0.574)	*(1.013)*	*(0.794)*
Punctuality	0.009	0.001	0.006
	(0.100)	*(0.106)*	*(0.132)*
Greenhouse Gas Emissions	0.178***	0.196***	0.134**
	(0.031)	*(0.035)*	*(0.043)*
PMs and NOx emissions (local pollutants)	0.127***	0.052	0.128**
	(0.033)	*(0.053)*	*(0.045)*
Log likelihood	-566.57	-356.96	-211.60
Observations	1743	1182	1026
AIC	1163.14	743.92	453.20

*** p<0.001, **p<0.05, *p<0.1. For an unrestricted model: the log likelihood was -1135.25 and the AIC was 2360.50.

Table 10. Mean willingness to pay estimates by user type.

	Never H2 Users	Occasional H2 Users	Frequent H2 Users
	Mean WTP	Mean WTP	Mean WTP
	C.I.	*C.I.*	*C.I.*
Frequency (increase of 1 minute between services)	0.103	0.083	0.159
	0.057 - 0.149	*(0.047 - 0.118)*	*(0.107 - 0.210)*
More comfort inside bus (Base: same comfort as now)	-	-	0.454
			(0.198 - 0.710)
Friendlier driver (Base: same friendliness as now)	-0.328	-0.341	-
	(0.051 - 0.604)	*(0.089 - 0.591)*	
Punctuality (decrease of 1 minute in tolerance from schedule)	0.117	0.104	0.089
	(0.057 - 0.176)	*(0.052 - 0.156)*	*(0.034 - 0.144)*
GHG (reduction of 10% from emissions of a diesel bus)	-	-	0.075
			(0.038 - 0.113)
PMs and NOx emissions (reduction of 10% from emissions of a diesel bus)	0.061	0.085	0.100
	(0.017 - 0.106)	*(0.050 - 0.121)*	*(0.061 - 0.140)*

Figure 1. Density response for DCE survey. Each dot represents a respondent. Kingswell Park & Ride and Bucksburn sites appear off-map (Sample Size = 338).

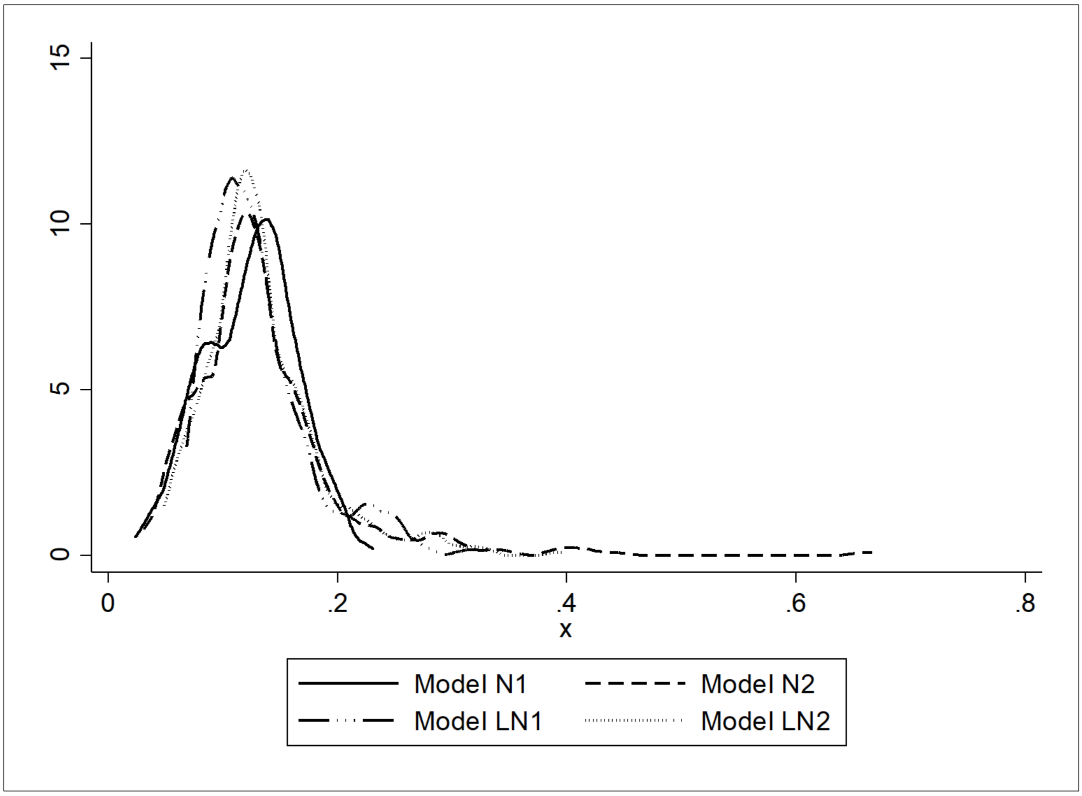

Figure 2. Kernel Densities WTP for frequency.

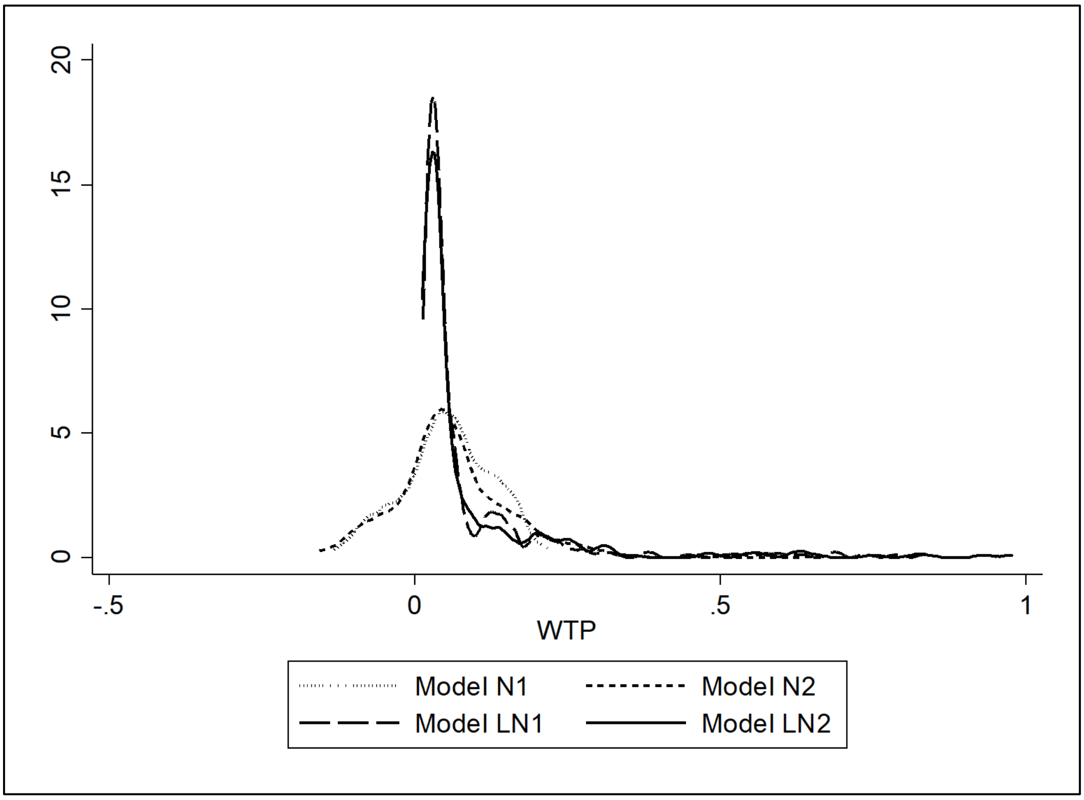

Figure 3. Kernel Densities WTP for GHG emissions.

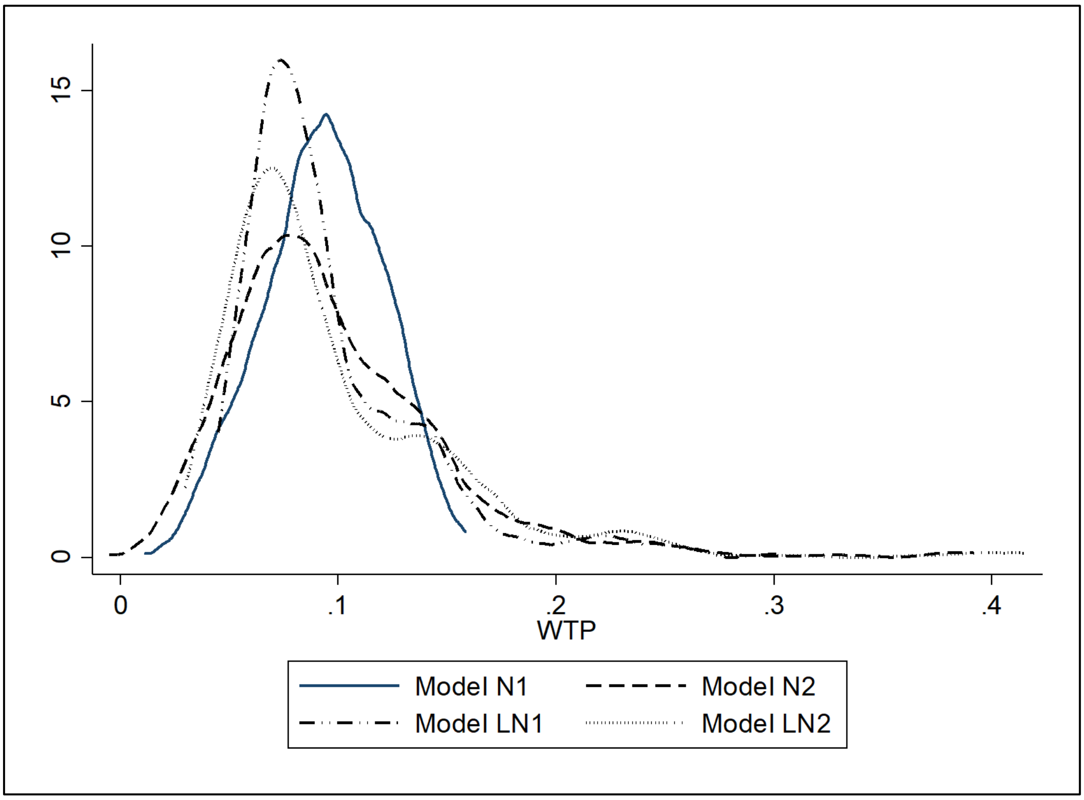

Figure 4. Kernel Densities WTP for local pollutant emissions.

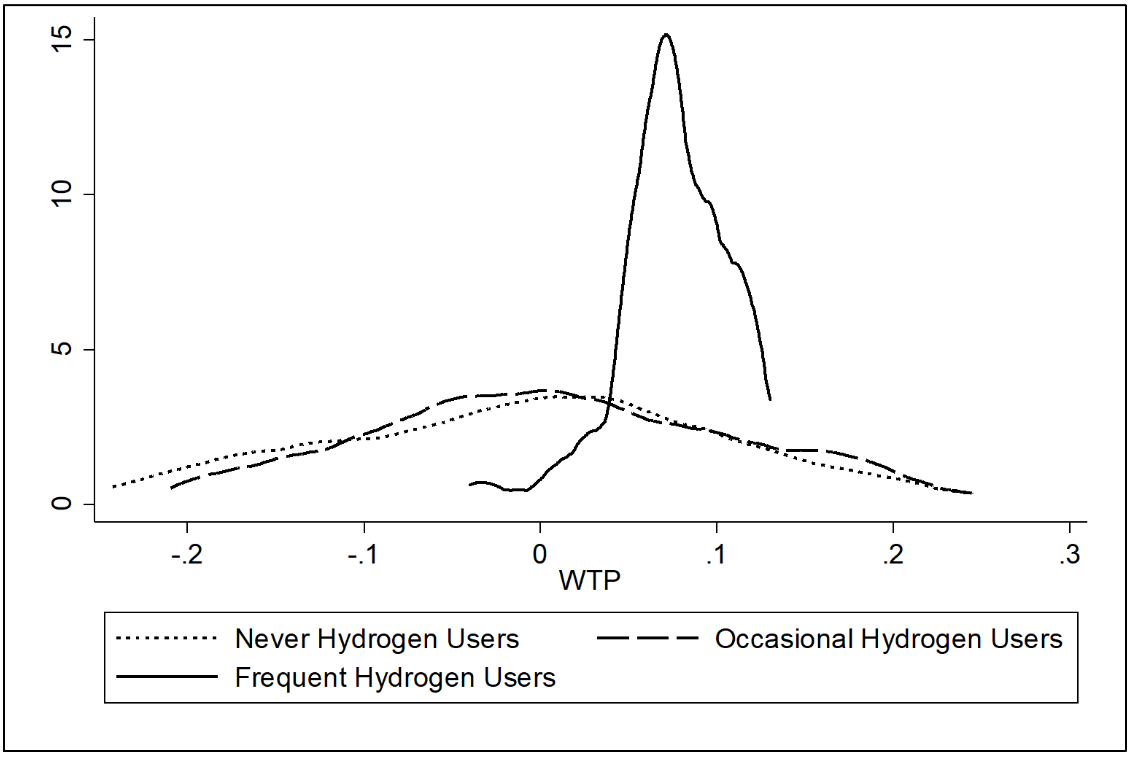

Figure 5. Kernel Densities WTP for reduced GHG emissions by bus user type.

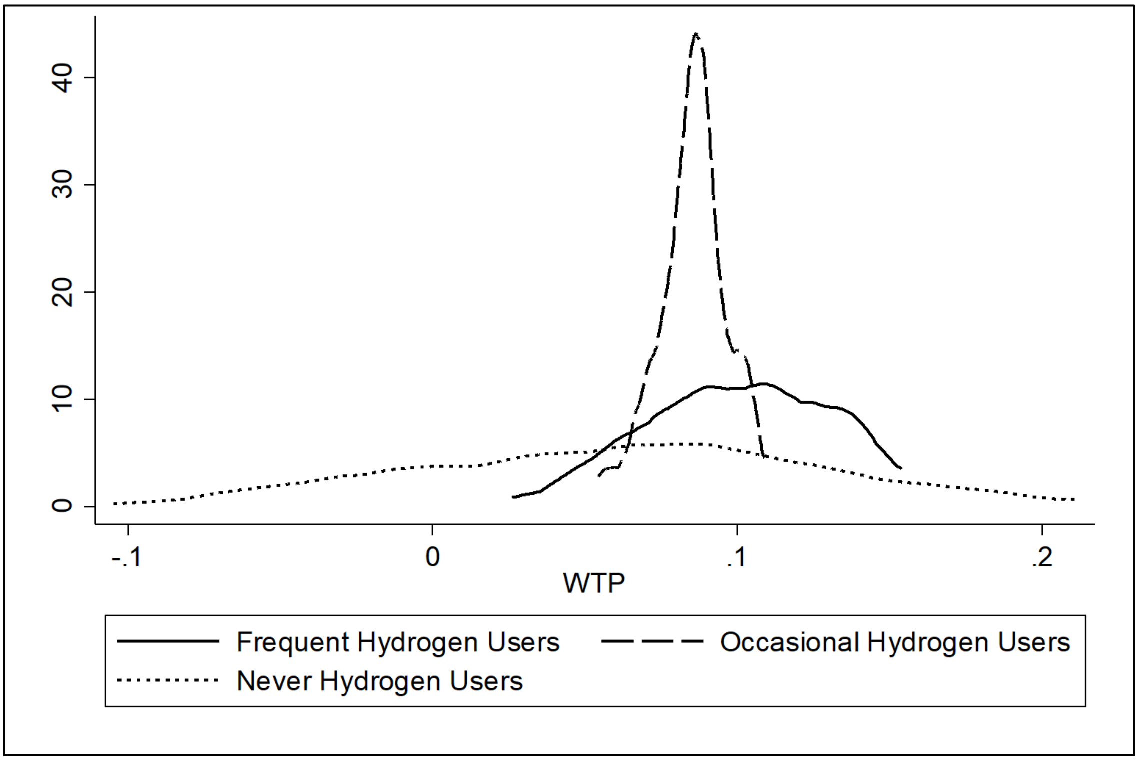

Figure 6. Kernel Densities WTP for reduced local pollutant emissions by bus user type.

Appendix A. DCEs that have explored emissions in private vehicles.

Author	Location	Used the AF technology	Used an emissions attribute	Framing of emission attribute
Beggs et al. (1981)	USA	✓		-
Calfee (1985)	USA - California	✓		-
Bunch et al. (1993)	USA - California		✓	Level of pollution relative to 1991 cars
Brownstone (1996)	USA - California		✓	Tailpipe pollution relative to new 1993 gasoline cars
Golob et al. (1997)	USA - California		✓	Generic tailpipe emissions
Ewing and Sarigöllü (2000)	Canada		✓	Pollution emissions as a percentage of present vehicles
Dagsvik et al. (2002)	Norway	✓		-
Adler et al. (2003)	USA - California	✓		-
Batley et al. (2004)	UK		✓	Generic emissions (scale of 1 to 10)
Horne et al. (2005)	Canada		✓	Percentage emissions compared to current vehicle
Potoglou and Kanaroglou (2007)	Canada		✓	Percentage of pollution relative to a present day average car.
Ahn et al. (2008)	South Korea	✓		-
Mau et al. (2008)	Canada	✓		-
Axsen et al. (2009)	Canada		✓	Pollution based on fuel efficiency levels
Dagsvik and Liu (2009)	China	✓		-
Caulfield et al. (2010)	Ireland		✓	Greenhouse gas emissions
Beck et al. (2011)	Australia		✓	Annual emissions charges (depending on fuel efficiency)
Eggers and Eggers (2011)	Germany	✓		-
Hidrue et al. (2011)	USA		✓	Pollution compared to the conventional gasoline vehicle
Mabit and Fosgerau (2011)	Denmark		✓	Pollution percentage from conventional vehicle
Qian and Soopramanien (2011)	China	✓		-
Achtnicht et al. (2012)	Germany		✓	CO2 emissions per kilometre (in grams of CO2 per km)
Hess et al. (2012)	USA - California	✓		-
Lebeau et al. (2013)	Belgium		✓	Ecoscore as a proxy of environmental performance
Link et al. (2012)	Austria		✓	CO2 emissions reductions in grams per kilometre

Maness and Cirillo (2012)	USA - Maryland		✓	Emission relative to an average 2010 vehicle.
Chorus et al. (2013)	Netherlands	✓		-
Daziano (2013)	USA - California	✓		-
Glerum et al. (2014)	Switzerland	✓		-
Hackbarth and Madlener (2013)	Germany		✓	CO2 emissions with respect to an average vehicle
Ito et al. (2013)	Japan		✓	Percentage reduction of carbon dioxide.
Jensen et al. (2013)	Denmark		✓	Carbon emissions
van Rijnsoever et al. (2013)	Netherlands		✓	Local emissions
Hoen and Koetse (2014)	Netherlands	✓		-
Kim et al. (2014)	Netherlands	✓		-
Tanaka et al. (2014)	USA & Japan		✓	Generic emissions compared to a gasoline vehicle
Axsen et al. (2015)	Canada	✓		-
Dumortier et al. (2015)	USA		✓	Car energy label as a proxy of environmental performance
Helveston et al. (2015)	USA & China	✓		-
Ščasný et al. (2015)	Poland	✓		-
Shin et al. (2015)	South Korea	✓		-
Valeri and Danielis (2015)	Italy	✓		-
Bahamonde-Birke and Hanappi (2016)	Austria	✓		-
Carteni et al. (2016)	Italy	✓		-
Dimitropoulos et al. (2016)	Netherlands	✓		-
Krause et al. (2016)	USA	✓		-
Rasouli and Timmermans (2016)	Netherlands	✓		-

Rudolph (2016)	Germany	✓		-
Zoepf and Keith (2016)	USA	✓		-
Cherchi (2017)	Denmark	✓		-
Cirillo et al. (2017)	USA - Maryland	✓		-
Higgins et al. (2017)	Canada		✓	CO2 tailpipe emissions (tonnes per year)
Sheldon et al. (2017)	USA - California	✓		-

Appendix B. DCEs with a bus travel alternative.

Authors	Location	Main objective	Attribute and level selection	Choice task alternatives	Attributes and Levels (for the bus alternatives if multi-mode)
Alpizar and Carlsson (2003)	Costa Rica	Transport mode choice	Qualitative research (focus groups) and a pilot survey.	2 alts (Bus v car)	Bus fare (CR Colones), Travel time (Same time as car, +20 mins, +30mins, +40 mins), Punctuality (Always on time, Bus sometimes more than 15 mins late), Distance to bus stop (10 mins, 15 mins, 20 mins), Number of departures (Every 5 mins, 10 mins, 15 mins), Comfort and security (Same as today, Program for Quality Improvement is implemented).
Axhausen et al. (2008)	Switzerland	Transport mode choice (assess VTTS)	Pre-testing using pilot survey	2 alts (Car v Bus or Rail)	Travel cost (Swiss Fr), Travel time (mins), Headway (mins), Number of changes (Integer)
Baidoo and Nyarko (2015)	Ghana	Transport mode choice	Discussions with experts and passengers	2 alts (Bus v Car)	Price (Yes, No), Comfort (Disagree, Agree, Noise level (Very low, High), Time (3pm - 6pm, 6am-9am), Habit (Yes, No)
Nyarko and Baidoo (2015)	Ghana	Bus Service Improvements	Discussions with experts and trip makers.	2 alts (different bus services)	Walking distance to bus stop (within 10 mins, more than 10 mins), Attitude of driver and mate (Very polite, Very impolite), Transport fare (Normal fare, 15% more), Bus stop facility (Shelter, lighting and seat; No seat or lighting or shelter), Reliability (On time, late).
Bhat and Sardesai (2006)	Austin, TX (USA)	Transport mode choice	Pilot Survey to test levels	4 alts (Drive alone, shared ride, bus rail) or 3 alts (if no access to car)	Usual door-to-door travel time (mins), Additional possible travel time (mins), Travel cost ($), Availability of a grocery store near station (Yes, no), Child Care near the station (Yes,no).
Eboli and Mazzulla (2008) and Cirillo et al. (2011)	University of Calabria (Cosenza, Italy)	Service Quality Index	Literature review and pilot survey	3 alts (2 unlabelled hypothetical buses and current bus)	Walking distance to bus stop (Current, +10 mins), Frequency (Every 15 mins, Current), Reliability (On time, late), Bus stop facilities (Bus shelter, seats and lighting, no shelter+no seats+no lighting), Bus crowding (No overcrowded, overcrowded), Cleanliness (Clean enough, Not clean enough), Fare (Current, +25%), Information (Timetable+map+announcement of delays, no timetable+no map+no announcement of delays), Transit personnel attitude (Very friendly, very unfriendly).
Espino et al. (2007)	Gran Canaria (Spain)	Transport mode choice	Qualitative research (focus groups) and a pilot survey.	2 alts (Bus v Car)	Travel time (Current, -25%, +25%), Cost, Bus Frequency (Current, -25%, -50%), Bus Comfort (Low, Standard, High)
Hensher (2014)	New South Wales (Australia)	Service Quality Index	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)
Hensher (2015)	New South Wales (Australia) & Singapore	Service Quality Index	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)

Hensher et al. (2003)	Sydney (Australia)	Service Quality Index	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)	Same as Prioni and Hensher (2000)
Hess et al. (2013)	Warwick, Manchester and Leeds (England)	Fare simplification	Pilot Survey	2 alts (different bus services)	Fare structure (Fixed, As now), Fare level (As now, +£), Journey time (mins)
Kelly et al. (2007)	British Columbia (Canada)	Transport mode choice (Resort visit amongst tourists)	Systematic review and stakeholder feedback.	3 alts (Rental car, Express Bus, Train, Opt out)	Availability of bus (Not available, Limited accessibility, Extensive accessibility), Fare (Canadian $)
Kumar et al. (2004)	Midnapur (India)	Bus Service Improvements	Premilinary investigation (not specified)	3 alts (different bus services)	In-vehicle travel time (mins), Travel cost (Rupees), Discomfort (Seating, Standing comfortably, Standing in crowd), Service headway (mins)
Lu et al. (2018)	UK	Bus Service Improvements	Based on UK Value of Travel Time Report	2 alts (two bus journes and an opt out)	Expected waiting time (mins), Expected journey time (mins)
Maitra et al. (2015)	Kokalta (India)	Bus Service Improvements	Pilot Survey to test levels	2 alts (different bus services)	Type of bus (mini bus, ordinary private bus, state bus), Waiting time at bus stop (mins), Comfort inside the bus (seat, standing comfortably, standing in congestion, standing at brush load condition), Traffic information (traditional way, using LED display, using LED display+real-time on-board information, using LED display+real-time on-board information +real-time using LED display at bus stop), Average journey speed (km/h), Fare (INR/km).
Marcucci and Gatta (2007)	Marche region (Italy)	Service Quality Index	Literature review and qualitative research (focus groups)	3 alts (2 unlabelled hypothetical buses and current bus)	Bus fare (Euros), Amount of delay at bus stop (mins), bus travel time (trip length - mins) bus frequency (number of buses per hour), availability (amount of time between service inception and closure - mins).
Phanikumar and Maitra (2007)	Kokalta (India)	Bus Service Improvements	Premilinary investigation (not specified)	4 alt (different bus services)	Travel comfort (standing in crowd, great seat during journey, congested seating, standing comfortably), Travel speed (km/h), Travel time (min/km), Waiting time (mins), External appearance (Good, average, poor), Noise level (Very low, Low, High, Very High), Travel Cost (Paise/km)
Prioni and Hensher (2000) Hensher and Prioni (2002).	New South Wales (Australia)	Service Quality Index	Obtained from a literature review (more detail in Prioni and Hensher (1999)) and a pilot survey	3 alts (2 unlabelled hypothetical buses and current bus)	Reliability (On time, 5 mins late, 10 mins late), Frequency (Every 15 minutes, Every 30 minutes, Every 60 minutes), Walking distance to bus stop (Same as now, 5 mins more, 10 mins more), Waiting safety (Very safe, Reasonably safe, Reasonably unsafe), Access to the bus (Wide entry with no steps, Wide entry with 2 steps, Narrow entry with 4 steps), Air conditioning (Available with no surcharge, available with a surcharge of 20% on existing one-way fare, Not available), Cleanliness of seats (Very clean, Clean enough, Not clean enough), Info at the bus stop (Timetable, Timetable and map, No timetable or map), Travel time (25% quicker than the current travel time, Same as now, 25% longer than current travel time), Bus stop facilities (Bus shelter with seats, Seats only, No shelter or seats at all), Fare (25% more than the current one-way fare, Same as now, 25% less than the current fare), Driver attitude (Very friendly, Friendly enough, Very unfriendly), Safety on board (The ride

					is very smooth with no sudden braking, The rise is generally smooth, The rise is jerky; sudden braking occurs often).
Rojo et al. (2012)	Burgos (Spain)	Transport mode choice	Previous surveys done in the region.	2 alts (Bus v Car or Rail)	Journey time (Current, -20%, +20%), Fare (Current, -20%, 20%) Number of daily services (Current, +20%, +50%), Condition of vehicle (Old, semi-new, new, high standard).
Román et al. (2014)	Gran Canaria (Spain)	Service Quality Index	Qualitative research (focus groups).	2 alts (current bus v unlabelled alternative)	Travel time (Mins), Price (Euros), Time between two services - Frequency (mins), Access to bus stops (mins), Delay (Ontime, +5 mins, +10 mins), Comfort (Standing during all the journey, Standing in part of the journey, seated during all the journey), Information at bus stop (Itinerary maps, Maps and timetable, electonic panels+maps+timetables), Shelter (Yes, no), Driver behaviour (Unpleasant treatment and aggressive driving, pleasant treatment and aggressive driving, pleasant treatment and smooth driving), Cleanliness (Poor, Normal, Good) - 6 attributes at a time.
Swanson et al. (1997)	London (UK)	Bus Service and Infrastructure Improvements	Defined by London Transport Authority (LT Buses) and qualitative research	2 alts (Current v improved service)	Divided into journey stages. 1. Pre-trip: Maps, Timetables, Customised local information, telephone information services; 2. Bus-stop infrastructure: Type of shelter, Type of seat, Lighting, Cleanliness and stat of repair; 3. Waiting at bus-stop: Fixed information display, Real-time information, Service reliability; 4. Bus at the kerbside: Compulsory or request stop, Ease of identifying correct bus, Stopping position of bus, Design of vehicle entry stops; 5. Encountering the driver: Driver appearance, Driver helpfulness, Driver identification, Availability of change; 6. Moving to your seat: Level of crowding, Design of luggage storage area, Seating configuration, Quality of vehicle motion; 7. Travelling in a seat: Types of seat, Spaciousness of seats, Type of ventilation, Cleanliness, Travel time; 8. Leaving the bus: Provision of information on the bus, Number and location of doors; Fare. (Use of pictures for majority of attributes)

Appendix C. Results from models estimated in willingness to pay space.

	Model W1 (500) Normal Distributions		Model W2 (500) Log-normal Distributions
	Mean WTP *(Standard Error)*	Mean WTP *(Standard Error)*	Median WTP *(Standard Error)*
ASC (Choose current service)	0.108	0.180*	0.180*
	(0.090)	*(0.085)*	*(0.085)*
Frequency (increase of 1 minute between services)	-0.119***	-0.126***	-0.107***
	(0.011)	*(0.011)*	*(0.010)*
More comfort inside bus (Base: same comfort as now)	0.073	0.086	0.077
	(0.061)	*(0.063)*	*(0.080)*
Friendlier driver (Base: same friendliness as now)	-0.156**	-0.157**	-0.154**
	(0.062)	*(0.064)*	*(0.070)*
Punctuality (decrease of 1 minute in tolerance from schedule)	0.113***	0.105***	0.099***
	(0.014)	*(0.013)*	*(0.017)*
GHG (reduction of 10% from emissions of a diesel bus)	0.051***	0.107**	0.017**
	(0.009)	*(0.039)*	*(0.007)*
PMs and NOx emissions (reduction of 10% from emissions of a diesel bus)	0.091***	0.092***	0.068***
	(0.008)	*(0.010)*	*(0.010)*
Fare (increase in £)	*0.567****	*-2.177****	*-2.177****
	(0.145)	*(0.452)*	*(0.452)*
Interaction Emissions (GHG*PMsNOx)	0.141***	0.123**	0.123**
	(0.043)	*(0.043)*	*(0.043)*
Standard Deviations			
Frequency	0.076***	0.078***	0.078***
	(0.014)	*(0.023)*	*(0.023)*
Comfort	0.116	0.036	0.036
	(0.172)	*(0.120)*	*(0.120)*
Driver Friendliness	0.073	0.034	0.034
	(0.158)	*(0.121)*	*(0.121)*
Punctuality	0.056*	0.037	0.037
	(0.029)	*(0.040)*	*(0.040)*
GHG	0.104***	0.652	0.652
	(0.012)	*(0.680)*	*(0.680)*
PMs and NOx emissions (local pollutants)	0.059***	0.084***	0.084***
	(0.012)	*(0.028)*	*(0.028)*
Fare	0.706**	2.000*	2.000*
	(0.249)	*(1.097)*	*(1.097)*
Log likelihood	-1177.26		-1182.54
Observations	3951		3951
AIC	2386.52		2397.09
BIC	2487.03		2497.59

Note: Estimates are WTP, except for fare that is the lognormal of the parameter estimate. Number of Halton draws in parenthesis.