Assessing residents' support for environmentally-friendly public transportation upgrades across Europe

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Abstract

The adoption of environmentally-friendly public transportation (EFPT) systems is targeted by European Union (EU) policies as a means to improve local ambient quality, reduce road congestion, and contribute to greenhouse gas (GHG) abatement. In support of this policy goal, this study assesses and compares public support for EFPT across 31 European nations. We develop a novel Bayesian logit model with identified scale to estimate willingness to pay (WTP) for local EFPT upgrades from 6,520 contingent valuation survey responses. We find evidence that WTP is primarily driven by expected improvements to public goods, such as air quality and GHG abatement, as opposed to private ridership benefits. Across all nations, an average WTP of €7.69 per household, per month is estimated. WTP distributions are strongly positive in all nations suggesting implicit public support for EFPT at the EU-level.

Keywords: Willingness to pay; Public transportation; Bayesian choice modeling; Clean buses; Energy transition

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1 Introduction

Gasoline and diesel fueled vehicles are still the world's dominant means of transportation in rural and urban areas (Hao et al., 2016). It is estimated that one-sixth to one-fifth of greenhouse gas (GHG) emissions are generated by these conventionally fueled vehicles (Hensher 2008, Fontaras et al. 2017). Emissions from fossil fuel vehicles can deteriorate local air quality and lead to various health problems, such as lung cancer (Guo et al., 2016), high blood pressure (Weichenthal et al., 2014), dementia (Chen et al., 2017) and premature deaths (Jerrett et al., 2013). Moreover, a continued reliance on conventionally fueled methods of transportation contributes to GHG emissions and inhibits climate change mitigation efforts.

Passenger travel via public transportation, including buses, railways, and trams or metros, reduces GHG emissions, congestion, pollution, and fuel use, compared to passenger travel with private automobiles (UITP, 2015). As such, European Union (EU) transportation policies target an increase in public transit ridership, and non-powered modes of transport such as walking and biking, with corresponding decreases in private automobile usage (EU, 2019; EC, 2013; Peters and Wainwright, 2017). Policy options for achieving a substitution of public transit use for private care usage include taxes and subsidies (Spiller et al., 2014; Rivers and Plumptre, 2018), improving quality, reliability and frequency of public transit (Chakrabarti, 2017), and enhancing the interconnections of public transit with other types of transport (Yan et al., 2019). The degree of roadway congestion also plays an important role in the substitution of public transit in lieu of private cars (Beaudoin and Lawell, 2018).

The EU urban mobility policies are meant to contribute to the overall EU ambition to reduce GHG emissions by at least 80% below 1990 levels by 2050 (Langsdorf, 2011). In the public transportation sector, a 10% renewable energy contribution to final energy demand is targeted in all member states (Wesselink et al., 2010). However, amongst all sectors in the EU the transportation sector is the only one whose GHG emissions share increased by a large margin; to 25% in 2017 compared to 15% in 1990 (European Commission, 2019).

Moreover, passenger transportation is expected to grow over the next decades (Capros et al., 2016). This development trajectory makes it critical to understand the usership dimension of public transit, green public transit options, and the costs and benefits to investing in new public transit infrastructure.

In Europe, the average passenger travels 13,505 km/year by motorized means (European Commission, 2019). Car travel accounts for 70.9% of distance travelled, while buses (7.4%), rail (6.8%) and trams/metros (1.6%) are the most used public transportation means (European Commission, 2019). The total expenditure on goods and services related to public transport is estimated at €130 to €150 billion per year, which accounts for 1-1.2% of the EU's GDP (UITP, 2015). Despite being a recent policy focus area, the European bus fleet still consists of 90% diesel or bio-diesel vehicles, and 50% of the fleet are older diesel designs that are significantly less efficient and more polluting than the newest diesel engines (UITP, 2015). Meanwhile, 54% of railways can support electric engines, whereas the balance still require conventionally-fueled trains (EU, 2016). This leaves ample room for technological improvements and movement towards alternative fuels in the European bus and train stock.

Environmentally-friendly public transportation (EFPT) options, such as electric and hydrogen buses, and electric trains, have gained a great amount of attention in many European regions in recent years. For example, London will introduce the world's first hydrogen-powered double decker buses by 2020, reducing the local and GHG impacts of over 10 million passenger journeys annually. In Rzeszow Poland, 140 solar-panelled bus stops are implemented to reduce energy consumption of public transportation stations. Vienna is adopting electric buses to create a cleaner and quieter downtown area. In 2019, Copenhagen replaced all diesel buses in the city to provide cleaner air in population-dense areas. These are microcosms for the broader EU policy push to de-carbonize public transport (EU, 2019; EC, 2013; Peters and Wainwright, 2017; EC, 2016).

Transforming or upgrading current transportation systems to become more environmentally-friendly can be costly. Electric and alternative fuel vehicles generally require higher upfront investments than comparable conventional vehicles, and can also require additional infrastructure (e.g. charge points), and additional personnel training in maintenance and operation (UITP, 2015). A shift towards EFPT only makes sense if the economic benefits outweigh the costs, and may require support from transit users and the public for the investment to be politically tenable.

Public support for EFPT upgrades will largely be due to the perceived benefits of the new EFPT system for the local citizenry. Oft-cited benefits from EFPT include reductions in local air and noise pollution, GHG abatement, and the potential for improved comfort for riders (UITP, 2015; Beaudoin et al., 2015; Galvis et al., 2015; Rivers and Plumptre, 2018). Lee et al. (2019) show that hydrogen (H_2) fuel cell (FC) buses are likely to result in reductions of overall energy consumption and air emissions compared to diesel buses. Similarly, Karlström (2005) finds environmental benefits from FC buses, including the reduction of atmospheric NO_x, particulates, and noise. Wall et al. (2008) show increasing urban accessibility and significant reductions in total NO_x and PM_{10} after the introduction of cleaner buses in Winchester, UK. Galvis et al. (2015) find that upgrading the technology of trains at railyards can have a substantial impact on local pollution levels, which the authors value at over $20 mil. per year in the case of one urban railyard in Atlanta, USA.

Any improvements to local air or noise pollution, and GHG mitigation from EFPT are non-market benefits that reduce the negative externalities of passenger travel. Estimating the value of these benefits therefore requires a non-market valuation approach. Past research has used the contingent valuation method (CVM), such as survey-based willingness to pay (WTP) studies. The few examples of WTP studies for EFTP include Haraldsson et al. (2006), who survey attitudes towards H_2 FC buses among passengers and drivers in Stockholm. The authors find that 64% of passengers are not willing to pay a higher fee to ride on H_2 FC buses. Saxe et al. (2007) also investigate the WTP for H_2 FC buses in Stockholm and find that passengers' WTP remained low even after one year of H_2 FC bus operation, possibly due to the already high bus fares in Stockholm. Heo and Yoo (2013) estimate WTP for a large-scale introduction of H_2 FC buses in South Korea and find an annual mean WTP of $4.55 per household per year in 2007. O'Garra et al. (2007) find a positive WTP for bus users ranging from €0.29 to €0.35 per single bus fare for H_2 FC buses in Berlin, London, Luxembourg and Perth. O'Garra and Mourato (2007) investigate respondents' WTP for large-scale introduction of H_2 buses in London and estimate a mean WTP of £7.32 in extra monthly bus fares for H_2 buses. Lin and Tan (2017) estimate a WTP for new energy buses of $0.09 per fare in the four most developed cities in China, while Tan and Lin (2019) find that people are willing to pay an additional amount of $0.13 per fare for new energy buses in China.[1]

The present study adds to this literature by analyzing the responses from a large-scale CVM survey of citizens' WTP for EFPT across 31 European nations. Closely related papers on WTP for EFPT upgrades are limited to municipal, or national settings, as discussed above, affording little opportunity to compare WTP and citizen preferences across regions. Furthermore, this limitation makes it impractical to design EU-level policies on the basis of current science. Therefore, the goal of the study is to assess and compare public support for upgrading transit fleets to EFPT across Europe. Respondents were asked if they would accept a monthly tax increase to upgrade the local public transit fleet with environmentally-friendly technology. The resulting 6,520 responses are analyzed via a novel statistical methodology that is introduced to the non-market valuation literature in this study, a Bayesian logit model with identified scale. The Bayesian logit model is an attractive alternative to classical methods, as it does not require invoking asymptotic theory to interpret estimation results. In the same vein, WTP predictions can be obtained from the Bayesian logit output without the need for asymptotic tools and second-stage methods to obtain standard errors. Furthermore, compared to maximum likelihood estimation (MLE), the Bayesian logit model is less sensitive to the choice of starting values, and less likely to 'get stuck' at local maxima.

For our analysis, we segment the respondents into groups based on their intensity of public transit use. Specifically, we identify non-users, and occasional, moderate, and heavy users of public transit based on self-reported usership from the survey. In the estimations containing all user types we find the counter-intuitive result that moderate and heavy users have lower WTP to support the implementation of EFPT despite the fact that they may

[1] The literature on WTP for alternative and cleaner fuel private vehicles is more extensive, including Lim et al. (2017), Liu (2014), Poder and He (2017), Rahmani and Loureiro (2019), and Noel et al. (2019).

be more likely to experience the private benefits of increased transportation comfort, while equally sharing in the improvements to local air quality. This suggests a protest response and potential status quo bias on the part of moderate and heavy users of public transport.

Therefore, we estimate a second model omitting moderate and heavy users, and find that the WTP of occasional transit users is indistinguishable from that of non-users. In addition to estimates based on user types, we estimate WTP as a function of respondent characteristics and find predominately positive effects from respondent perceptions of renewable energy and their self-proclaimed level of environmentalism. Overall, the model predicts an average WTP value of €7.89 per household, per month across the sampled nations. The predicted posterior distributions of WTP in each nation are substantially positive suggesting that non-market benefits from EFPT upgrades exist and are perceived by citizens. Comparable results are obtained from the model estimated on all user types. Predicted WTP across the sample nations is interpreted with respect to local air pollution levels to show that these values approximate a marginal damages curve from air pollution in Europe.

The balance of this paper is structured as follows: Section 2 describes the Bayesian model; Section 3 presents the empirical analysis including the survey instrument. Section 4 contains the results, which are followed by the overall conclusions.

2 Methodology

2.1 Bayesian logit with identified scale

In our application, each respondent is shown one bid value b_i, and asked if they would pay this bid in the form of a monthly tax increase in order to upgrade the local public transit fleet to EFPT. The observed yes(1) or no(0) response of person i, y_i for accepting a stipulated bid (tax) or not is related to an underlying latent WTP, y_i^* with the following rule:

$$
\begin{aligned}
&y_i = 1 \quad \text{if} \quad y_i^* > b_i \\
&y_i = 0 \quad \text{otherwise}
\end{aligned}
\tag{1}
$$

Latent outcomes (y_i^*) are then modeled as a linear function of regressors and coefficients, with a standard logistic error term. The scale parameter of the logit and its deviation is identified due to the presence of bids offered to respondents. These parameters are usually set to one. Instead, we generalize the logit model with scale parameter s, given as:

$$
\begin{aligned}
&y_i^* = \mathbf{x}_i'\boldsymbol{\beta} + \epsilon_i, \quad \text{with} \\
&\epsilon \sim log(0, s), \quad \text{and} \\
&\text{prob}(y_i^* > b_i) = \frac{1}{1 + exp\left(\tilde{b}_i - \tilde{\mathbf{x}}_i'\boldsymbol{\beta}\right)} \\
&\text{prob}(y_i^* \leq b_i) = \frac{1}{1 + exp\left(-\tilde{b}_i + \tilde{\mathbf{x}}_i'\boldsymbol{\beta}\right)}
\end{aligned}
\tag{2}
$$

where $\tilde{b}_i = b_i/s$ and $\tilde{\mathbf{x}}_i = \mathbf{x}/s$. $\mathbf{x}_i$ is a vector of explanatory variables for person i. Vector $\boldsymbol{\beta}$ includes all model coefficients. The last two lines in (2) make use of the fact that if $\epsilon_i \sim log\,(0, s)$ it follows that $\tilde{\epsilon}_i = \epsilon_i/s \sim log\,(0, 1)$, and $\tilde{y}_i^* = y_i^*/s \sim log\,(\tilde{\mathbf{x}}_i'\boldsymbol{\beta}, 1)$.

Defining the entire vector of n responses from all survey participants as $\mathbf{y}$, the sample likelihood is given as:

$$
\begin{aligned}
&p(\mathbf{y}|\boldsymbol{\beta}) \propto \\
&\prod_{i=1}^{n} \left(\frac{1}{1 + exp(\tilde{b}_i - \tilde{\mathbf{x}}_i'\boldsymbol{\beta})}\right)^{y_i} \left(\frac{1}{1 + exp(-\tilde{b}_i + \tilde{\mathbf{x}}_i'\boldsymbol{\beta})}\right)^{1-y_i}
\end{aligned}
\tag{3}
$$

Then, a standard normal prior for $\boldsymbol{\beta}$, with mean vector $\boldsymbol{\mu}_0$ and variance matrix $\mathbf{V}_0$ produces the following posterior kernel.

$$p(\boldsymbol{\beta}|\mathbf{y}) \propto exp\left(-\frac{1}{2}\left(\boldsymbol{\beta}-\mu_0\right)'\mathbf{V}_0'\left(\beta-\mu_0\right)\right)*$$
$$\prod_{i=1}^{n}\left(\frac{1}{1+exp(\tilde{b}_i-\tilde{\mathbf{x}}_i'\boldsymbol{\beta})}\right)^{y_i}\left(\frac{1}{1+exp(-\tilde{b}_i+\tilde{\mathbf{x}}_i'\boldsymbol{\beta})}\right)^{1-y_i} \tag{4}$$

This does not yield a tractable Gibbs Sampler (GS) with draws from a known distribution. Augmenting the model with draws of the latent data y^*, the standard approach in a Bayesian *probit* framework, does not solve the problem either as the resulting conditional posterior $p(\boldsymbol{\beta}|\mathbf{y}^*)$ remains unknown.

Holmes et al. (2006) suggested instead a data-augmented scale-mixture-of-normals approach that reinstates normality of the latent error ϵ_i, with heteroskedastic variances λ_i. These variance terms, upon proper transformation, follow a Kolmogorov-Sirnov(KS) distribution. As shown in Andrews and Mallows (1974), this is equivalent to the desired (marginal) logistic distribution for the latent errors as shown in (2). In mathematical terms:

$$\begin{aligned}
&\tilde{y}_i^* = \tilde{\mathbf{x}}_i'\boldsymbol{\beta} + \tilde{\epsilon}_i, \quad \text{with} \\
&\tilde{\epsilon}_i \sim n(0,\lambda_i), \\
&\lambda_i = (2\phi_i)^2, \\
&\phi_i \sim KS, \quad \text{with} \quad F(\phi_i) = \sum_{m=-\infty}^{\infty}(-1)^m exp(-2m^2\phi^2)
\end{aligned} \tag{5}$$

where $n(\cdot)$ denotes the normal density, and $F(\cdot)$ is the cumulative distribution function (cdf) of KS, that is the limiting distribution of the KS test statistic. While the pdf and cdf of the KS are only known to infinite series, such that their exact evaluation is not possible in the finite, one can nonetheless generate random draws from this density efficiently as discussed in Devroye (1986), and outlined below.

Practical implementation of this model via a Bayesian posterior simulator is facilitated by working with the squared scale s^2, as this allows for the use of standard priors for all model parameters. Specifically, we specify a prior for s^2 by choosing an inverse-gamma density with shape ν_0 and scale τ_0, that is:

$$p(s^2) \propto (s^2)^{-(\nu_0+1)} exp(-\frac{\tau_0}{s^2}) \tag{6}$$

The fully augmented, fully conditioned model can now written as:

$$\begin{aligned}
&p(\boldsymbol{\beta}, s^2, \mathbf{y}^*, \boldsymbol{\lambda}|\mathbf{y}) \propto p(\boldsymbol{\beta})p(s^2)p(\boldsymbol{\lambda})p(y^*|\boldsymbol{\beta}, s^2, \boldsymbol{\lambda})p(\mathbf{y}|\mathbf{y}^*) = \\
&(2\pi)^{-k/2}|\mathbf{V}_0|^{-1/2} exp\left(-\frac{1}{2}(\boldsymbol{\beta}-\boldsymbol{\mu}_0)'\mathbf{V}_0^{-1}(\boldsymbol{\beta}-\boldsymbol{\mu}_0)\right) * \\
&(s^2)^{-(\nu_0+1)} exp\left(-\frac{\tau_0}{s^2}\right) * \\
&\prod_{i=1}^{n} \frac{1}{4}\lambda_i^{-1/2} KS(\frac{1}{2}\lambda_i^{1/2}) * \\
&(2\pi)^{-n/2}(s^2)^{-n/2}|\boldsymbol{\Lambda}|^{-1/2} exp\left(-\frac{1}{2}(y^*-\mathbf{X}\boldsymbol{\beta})'(s^2\boldsymbol{\Lambda})^{-1}(y^*-\mathbf{X}\boldsymbol{\beta})\right) * \\
&\prod_{i=1}^{n} (I(y_i=0)I(y_i^* \leq b_i) + I(y_i=1)I(y_i^* > b_i))
\end{aligned} \tag{7}$$

where $\mathbf{X}$ is the n by k data matrix, $\boldsymbol{\Lambda}$ is a diagonal matrix with variances λ_i on the diagonal, $\boldsymbol{\lambda}$ is a vector that stacks all individual's λ_i and I is the indicator function. We use the fact that $\mid s^2\boldsymbol{\Lambda} \mid^{-1/2} = \left(s^2\right)^{-n/2} \mid \boldsymbol{\Lambda} \mid^{-1/2}$ in the fifth line of (7). The detailed steps of the GS are shown in the Appendix.

2.2 Posterior predictions of WTP

The GS yields the draws from the posterior distribution given in (7). The posterior predictive distributions (PPD) of *expected* WTP for respondents in a given country can be obtained as follows: For each draw of $\boldsymbol{\beta}$ from the GS, we can compute the vector of WTP for all respondents from that country as $\hat{wtp}_c|\boldsymbol{\beta}_c = \mathbf{X}_c * \boldsymbol{\beta}$ where c denotes a specific country. We then average these expected WTP predictions over all respondents in country c. We repeat this computation for all countries in our sample.

The PPD for the full WTP, which includes the effect of unobservables, can be derived as follows. Within one specific country, compute the vector of expected WTP as before. In a second step, draw a country-vector of latent WTP from the logistic distribution with expectation $\hat{wtp}_c$ and scale s, where s is the scale parameter obtained from the same iteration of the GS as the coefficient vector $\boldsymbol{\beta}$. The vector of full WTP predictions can then be averaged over all respondents from a given country to obtain country-level predictions.

3 Empirical Analysis

3.1 Survey Design

The survey data were collected during 2018 in all 28 EU countries along with three additional European countries: Switzerland, Turkey and Norway.[2] Respondents were provided with the survey via the internet in their native language, and all monetary values were converted from Euros to the equivalent value of native currency. Respondents were compensated with €5 for a complete survey, with an average completion time of approximately 20 minutes. A representative sample from each nation's population was ensured via quota sampling methods in the dimensions of income, age, and gender. The spatial distribution of 7,349 respondents who answered the WTP question is shown in Figure 1, showing the good geographic representativity of the sample. The final estimation sample for WTP elicitation is 6,520 individuals, after removal of protest responses as described below.[3] Table 8, in the Appendix, verifies a representative sample from each nation's population via quota sampling methods in the dimension of income, age and gender.

`[Figure 1 spatial location of respondents]`

There exist numerous WTP elicitation methods in contingent valuation analysis including open-ended questions, payment card, single-bounded dichotomous choice (SBDC) and

[2]For the full English survey text and dataset please see Reichl et al. (2019).

[3]The full survey has 18,037 questionnaires collected online, from which we are able to identify the approximate location of 14,691 respondents based on provided postal codes. 7,349 of these respondents answered the per-month tax contingent valuation question; the others were asked a valuation question based on per-ticket fare increases that is not considered here.

double-bounded dichotomous choice (DBDC) (Phaneuf and Requate, 2016). The two dichotomous methods are frequently used by CVM practitioners due to the simplicity of data collection, as well as statistical efficiency considerations (Hanemann et al. 1991, Bateman et al. 2002). Our CVM follows the classic SBDC setup (Hanemann, 1984). We prefer the SBDC method to avoid the anchoring, path and negation issues that arise with double-bounded and other forms of CVM (e.g. Cooper et al., 2002; Bateman et al., 2001; McLeod and Bergland, 1999). The CVM formulation follows O'Garra and Mourato (2007); O'Garra et al. (2007), and Neves and Mourato (2004), and the actual valuation question is reproduced in English in Table 1.[4]

`[Table 1 text of the CVM question]`

Bid value levels were designed based on previous literature (O'Garra et al. 2007, Lin and Tan 2017, Heo and Yoo 2013, Neves and Mourato 2004). Specifically, per month tax values are informed by the WTP for hydrogen buses with tax increases found in South Korea of about 3.85 euro per year (Heo and Yoo, 2013), and from the study of four cities in Neves and Mourato (2004) and O'Garra and Mourato (2007). Respondents to the work in Neves and Mourato (2004, Table 7), had WTP between 13-200 (€2005) per year for an EFPT bus fleet.[5] The cities included in the Neves and Mourato (2004) sample are London, Perth, Luxembourg and Berlin, which are all developed cities and three of them are in Europe. As such, we consider this sample as a good starting point for bid construction for our survey of 31 European nations, with the exception of the lower income nations in Europe who are not represented in the Neves and Mourato (2004) sample. In our bid construction we thus enhance the number of values at the lower end of the WTP distribution, and include a bid of zero to test for protest responses.

The observed annual WTP distribution across the four cities in Neves and Mourato (2004, Table 7) is summarized, converted to monthly 2018 Euro values, and rounded to

[4]The actual nature of transportation improvement was not described in detail, which leaves room for user-respondents to imagine private benefits. Similarly, the reduction in air pollution was left to respondents' imagination as well, which makes the exact interpretation of obtained WTP estimates difficult to determine.

[5]The outlier max WTP from Neves and Mourato (2004, Table 7) of €2,250 from London is removed for our construction of bids, as done in O'Garra et al. (2007)'s use of the data.

give the bid values shown in Table 2. Each nation in our sample received the same bid value schedule, but translated into their native currency where applicable using 2018 exchange rates. Differences in purchasing power across the nations are controlled for in the econometric models with country fixed effects and respondent income variables. The proportions of respondents who accept the bid in each country are provided in Table 2. As can be seen from the table, the percentage of positive responses decreases monotonically over the increasing bids with few exceptions, which is consistent with the intuition that people are more likely to agree to lower bid values, and suggests that our bid schedule approximates the underlying WTP distribution in most nations.

[Table 2 bid values and % of YES]

Respondents who reply 'no' to a zero bid value were viewed as protest responses, and dropped from the initial sample of 7,349. Similarly, we also dropped observations with missing values for degree days and PM_{10}, as temperature and air pollutant data are missing for some respondents, leaving 6,520 respondents for estimation. Table 2 also presents the total number of respondents and the total number of protest responses for all countries. As is evident from the table, there are only 112 respondents who were identified as protest responses, a much lower proportion of protesters to the proposed tax increase than the 26% and 42% for Perth and London-based samples, respectively, found in O'Garra et al. (2007).

3.2 Sample and Variable Description

In addition to the CVM question, we utilize two parts of the survey for this research. One part focusing on respondents' socio-economic and socio-demographic characteristics, including gender, age, household size, employment status, education, years of residence at the current address, and number of children, and a second part relating to respondent attitudes towards their current public transportation system and environmental issues, such as renewable energy and climate change.

In addition to the survey data, we also collected location-specific variables based on the respondents' self-reported postal code.[6] The location-specific data include elevation, number of different public transportation stations (bus stations, bus stops, railway stops, railway stations and tram stops), urban landcover percentage, temperature, precipitation, and air pollution (PM_{10}).[7] For temperature, precipitation and PM_{10}, we identify the three nearest monitoring stations to each respondent in relation to their postal code centroid. We then calculate the inverse-distance weighted average of data provided by these three stations. As pointed to by Büyükalaca et al. (2001), the metric of degree-days is a well-established tool for analyzing energy consumption that captures non-linearities in the effect of temperature change. We thus transform the temperature data to heating degree days (HDD) and cooling degree days (CDD). Based on Blázquez et al. (2013), the calculation of HDD and CDD statistics are given as (15) and (16) in the Appendix.

In order to capture the density of the public transportation system around each individual, we draw a 5km buffer around each respondent based on the centroid of the collected postal code and then count the numbers of different public transportation stations within this buffer. Following Haghshenas and Vaziri (2012), we then normalize the number of stations for each transportation mode. This produces an index ranging from zero to one for each transportation mode. These indexes are summed together to measure the intensity of public transportation infrastructure around each respondent. The composite index is calculated as follows:

$$index = \frac{T - min(T)}{max(T) - min(T)} \tag{8}$$

where T is the number of stations for one transportation mode within the 5km buffer of a respondent.

In order to measure the influence of elevation in public perceptions of energy consumption (Attari et al., 2010), we calculate the average elevation within the 5km buffer for each respondent. Liu and Shen (2011) find a significant effect of urban land use on the

[6]The sources of location-specific variables are given in the Appendix
[7]PM_{10} describes fine inhalable particles with diameters that are generally 10 micrometers and smaller.

transportation energy consumption in the metropolitan area of Baltimore. We follow these authors and similarly calculate the percentage of urban landcover within the 5km buffer for each respondent to investigate the influence of urban landcover on people's choice of contributing to a cleaner public transportation fleet.

`[Table 3 definitions of variables]`

Table 4 summarizes the percentages of categories for socio-demographic variables and Table 5 shows the respondent attitudes towards current public transportation, climate change and renewable energy. There are 40% of respondents who are satisfied with the current public transportation systems in their areas. In contrast, only 24% of respondents consider the current public transportation system to be environmentally-friendly. This is consistent with the high percentage of respondents who are willing to pay a non-zero tax for upgrading the public transportation from Table 2. A large share of respondents (64%) consider themselves to be pro-environmental, and an even larger share (83%) consider renewable energy to be beneficial for the environment, but only 56% believe that renewable energy will create jobs.

`[Table 4 percent of categories for socio-demographic variables]`

Moreover, respondents are categorized into four different groups based on their self-reported intensity of public transit use, as measured by the number of trips per week as shown in Table 5. The categories are non-users (zero trip per week), occasional users (one to four trips per week), moderate users (five to eight trips per week) and heavy users (over nine trips per week). Among all 6,520 respondents, there are 58% non-users, 19% occasional users, 9% moderate users, and 13% heavy users.

`[Table 5 percent of categories for attitudes variables]`

Table 6 presents summary statistics for continuous variables, such as PM_{10} pollution for the months of July and January, total HDD and CDD, annual precipitation, mean elevation, transportation density index, landcover percentage, total daily minutes of public transportation use, and monthly income. Total daily minutes of public transportation use are calculated based on respondents' time spent on four transportation modes (bus, train, tram or streetcar, underground). Following Harrison et al. (1997) and Terzi et al. (2010), PM_{10} pollution is captured for both summer and winter, as these two measures may have different effects on respondents' WTP to upgrade to a cleaner transportation fleet. As is evident from the table, total HDD are higher than total CDD, indicating that, in general, heating systems are likely more important for the typical European household than cooling systems (Aebischer et al., 2007). Adding to income information in Table 4, Table 6 shows that monthly income per individual household member has a mean of €1,278 with a large standard deviation of €1,048, indicating high income variability in our sample.

[Table 6 summary statistics for continuous variables]

3.3 Estimation Results

To fully investigate influences of explanatory variables and, ultimately, predict overall WTP for upgrading to EFPT in all 31 countries, we apply the Bayesian logit with identified scale model. We further distinguish between a specification that includes all user types (non-users, occasional users, moderate users and heavy users) and a specification that omits moderate and heavy users for the reasons discussed above. We will refer these two model specifications as "Model 1" and "Model 2", respectively.

For our GS, we choose a typical normal prior for $\boldsymbol{\beta}$ with a mean vector of zero and a diagonal covariance matrix with variances set to 100, and an inverse-gamma prior with shape $\nu = \frac{1}{2}$ and scale $\tau = \frac{1}{2}$ for the scale parameter, s^2. Furthermore, we use the ordinary least square (OLS) estimation results, as starting values for $\boldsymbol{\beta}$ and s^2, respectively. To ensure the effect of starting values is negligible, we discard the first 100,000 draws of the GS sequence as "burn-ins", and keep the remaining 1,000,000 draws for inference.

We provide three posterior statistics: posterior mean, posterior standard deviation, and the proportion of the posterior distribution that exceeds zero. As explained in Cohen et al. (2016b), the last statistic provides an at-a-glance assessment if a given variable has a predominantly positive ($p > 0$ is close to one), negative ($p > 0$ is close to zero), or an ambivalent ($p > 0$ is close to 0.5) effect. In a slight abuse of classical terminology, we will consider variables that have at least 90% of posterior distribution on the right-hand or left-hand side of zero ($p > 0$ is more than 0.9 or less than 0.1) as 'statistically significant'.

Both specifications include 30 country fixed effects terms for capturing unobserved country effects with Austria as the omitted nation. We also include in each specification two age categories with the age group of 18-34 taken as the baseline. Similarly, the "basic education" group (elementary or secondary education) and those who have resided at the current address for less than 5 years are omitted as baseline categories. In all specifications, we include attitude variables as shown in Table 3. With the inclusion of the attitudinal variables we test if a respondent's underlying beliefs about renewable energy and the environment influence their WTP for upgrades to EFPT.

`[Table 7 estimation results for Model 1 and Model 2]`

The left side of Table 7 presents the estimation results for Model 1. The posterior mean of the coefficients related to moderate and heavy users are strongly negative. This finding is thought to be counter-intuitive, as moderate and heavy users are at least equally likely to benefit from air quality improvements, and may perceive greater benefits from any improvement to comfort from the upgraded public transportation fleet compared to less frequent users. As pointed out by Linnerud et al. (2019), this counter-intuitive result may be due to a status quo bias where strong preferences for the current state of affairs can hamper support for the energy transition. In our case, moderate and heavy users' relative reluctance to support an EFPT may be fueled by concerns about potential changes to routing or frequency of public transport options, or as a protest to current fare prices. In any case, due to the counter-intuitive findings regarding moderate and heavy users, we refrain from discussing any further results produced by Model 1, and turn our attention instead to Model 2, which omits the moderate and heavy users segment.

The right side of Table 7 illustrates the estimation results for Model 2, which uses observations from only occasional and non-users of public transit. As we see from the table, the posterior mean of occasional users is positive but the $p > 0$ is close to 0.5, indicating that occasional users' WTP is indistinguishable from that of non-users. This suggests that WTP for EFPT from these two groups is driven by expected improvements to public goods, such as reductions in local air and noise pollution and climate change mitigation. Among the location-specific variables, the effect of urban landcover percentage on WTP stands out as strongly negative ($p > 0 = 0.064$). This suggests that respondents in dense urban areas have lower WTP for EFPT upgrades than those in more rural areas. In contrast, the effects of degree days, public transit density, annual precipitation, and elevation are vague and of small magnitude. The other spatial variable showing nearly a 'significant' effect is summer PM_{10} pollution levels ($p > 0 = 0.80$). The estimated effect suggests that respondents in areas with higher summer pollution have higher WTP for EFPT upgrades. This is consistent with increasing marginal damages from air pollution (Phaneuf and Requate, 2016).

In contrast, the attitudinal variables show considerable influence on respondent WTP. Environmentalist attitudes, as measured in the self-reported variable 'environ_pro', raise monthly WTP by €2.50, on average, representing a ~33% higher WTP from this population segment. The belief that renewable energy project create jobs has a similarly substantial and positive effect on WTP. Interestingly, this effect is more than double in magnitude than the estimated increase of WTP from the belief that renewable energy improves the environment, which points to the importance of ancillary economic boons and job creation in gaining support for the energy transition, as suggested by previous work (Cohen et al., 2016a). Respondents who are uncertain that climate change is actually happening have a substantially lower WTP. This is consistent with the interpretation of WTP for EFPT upgrades as largely driven by WTP for improving the quality of public goods. From this result we estimate that ~12% of average monthly WTP is driven by the perceived climate mitigation benefits of EFPT.

Furthermore, perceptions of the current public transit fleet in their area is shown to influence respondent WTP for upgrades. The perception of the current level of environmentally-friendly technology in the fleet is weakly associated with lower WTP. This is consistent with diminishing marginal returns to technology upgrades. The level of satisfaction with the current public transit system has a moderate positive effect on WTP. This may reflect an approval of public transit managers and trust that the new tax revenues will be well used in upgrading to EFPT.

For socio-demographic respondent characteristics, the effect of the number of children is strongly positive with substantial magnitude. This indicates that respondents with more children are more likely to support the introduction of EFPT, which may be driven by concerns over their children's health or future environmental consequences from public transport. Older respondents (over 55) have a higher WTP, which is in contrast to past findings in energy research showing that older groups are less willing to adopt new technologies (Willis et al., 2011; Claudy et al., 2011). The effect of monthly income is strongly positive, suggesting that EFPT, and associated ambient quality, follows the income effect of a normal good. Other socio-demographic control variables including, employment status, education level, and time living in the area do not show clear effects on WTP for EFPT upgrades.

3.4 WTP predictions

WTP predictions are calculated for each nation in the sample and the sample average, using the method described in section 2.2. The numerical results are given in terms of Euros/month per household for both Models 1 and 2 in Tables 9 and 10 in the Appendix. Predicted WTP distributions are described by their mean, lower bound, and upper bound.[8] All three quantites of predicted WTP are positive in all countries, indicating respondents are generally willing to support the implementation of EFPT with additional tax contributions. We note that the predicted expected WTP and predicted full WTP are approximately equal in Tables 9 and 10, which is consistent with the small estimate of scale shown in the model estimation results. Given these similarities, we will focus on the predicted full WTP in the following discussion. Figure 2 shows the PPDs of WTP for Models 1 and 2 averaged across all nations, and observations, in the respective samples. Model 1, including heavy

[8]The lower and upper bound are the highest posterior density interval which captures the smallest area of 95% posterior density.

and moderate users of public transit, gives a narrower, left-shifted predicted WTP density compared to that from Model 2. Mean WTP from Model 1 is €7.46, and mean WTP from Model 2 is €7.89. This is consistent with the negative coefficient estimates for moderate and heavy users in Model 1, Figure 2 shows that including moderate and heavy users in the model results in small decreases in WTP predictions.

`[Figure 2 PPD of predicted full WTP for Model 1 and Model 2]`

The graphic representations of predicted WTP based on Model 2 are given in Figure 3 and Figure 4.[9] In these two figures, a dashed vertical line at zero is superimposed in each subplot. These figures clearly show that the predicted WTP distributions for most countries are located to the right of zero, indicating a predominantly positive WTP for the introduction of EFPT. Also, it is worthwhile to notice that the shapes of these predictive densities are similar across nations, except for Cyprus, Greece and Romania, which exhibit more diffuse WTP distributions in both model specifications.

`[Figure 3 The WTP distribution of Model 2:  first 16 countries]`

`[]Figure 4 The WTP distribution of Model 2:  second 15 countries]`

In addition to numerical values and graphical representations of predicted WTP, it is also of interest to analyze the relationship between predicted WTP and air pollution intensity. Figure 5, generated based on the predicted full WTP of Model 2, illustrates the relationship between mean WTP, expressed as a percentage of median income for each country, and average annual PM_{10} concentrations related to the respondents from each nation. The percentage of WTP relative to median income is clearly increasing with PM_{10} concentration, suggesting that differences in air pollution is a driver of international heterogeneity in WTP. The fitted curve superimposed on the figure can be interpreted as a marginal damages curve. This interpretation is bolstered by the finding above that non-users and occasional users have indistinguishable WTP for EFPT upgrades, which suggests that WTP is largely

[9] The graphical representations of predicted WTP based on Model 1 are given in the Appendix, in Figure 6 and Figure 7.

driven by perceived improvements to public goods rather than private ridership benefits. The positive slope of the estimated marginal damages curve in Figure 5 suggests that a higher pollution level leads to higher relative WTP; that is, societal benefits from marginal improvements to air quality are greater when air pollution levels are higher.

`[Figure 5 for WTP prediction to income and air pollution Model 2]`

4 Conclusion

This study provides the first systematic analysis of WTP for upgrading existing local public transportation fleets with environmentally-friendly technology across 31 European countries. WTP is estimated from a contingent valuation survey of 6,520 respondents, asking them if they would agree to a specified monthly tax increase to upgrade the local public transit fleet. Methodologically, we contribute to the choice modelling literature with a novel Bayesian logit estimation framework with identified scale.

We estimate two specifications of the Bayesian logit model, first including all respondents, and then including only occasional and non-users of public transit. In the first specification we find the counter-intuitive result that moderate and heavy users of public transit have lower WTP than non-users. This is likely due to status quo bias and strategic behavior on the part of heavy and moderate users. A further complication in the analysis of consistent users of public transit is the heterogeneity in fare prices. As discussed in Saxe et al. (2007) high fare prices may drive protest responses and strategic behavior relating to transit system upgrades. A similar result is found for Berlin bus users in O'Garra et al. (2007).[10] Due to the wide geographic scope of our study and the heterogeneity in European public transit fares, including associated subsidies, special tickets, and temporary offers, the inclusion of fare prices in our analysis is infeasible. Instead, we rely on self-reported satisfaction with the local public transit system, which shows a strong positive effect on WTP. Nevertheless, our findings reiterate the takeaway from O'Garra et al. (2007) and

[10] Additionally, O'Garra et al. (2007) do not include transit intensity in their models of WTP a monthly tax increase, perhaps due to difficulties with response behavior associated with this dimension.

Saxe et al. (2007), that status quo and response bias is a true concern for stated preference practitioners working in public transit.

The second model specification omits responses from moderate and heavy users of public transit and shows that the WTP of occasional users is indistinguishable from that of non-users. This suggests that WTP is primarily driven by expected improvements to public goods, such as ambient quality and climate change mitigation, as opposed to private ridership benefits, such as comfort. Regardless of model specification, the minimum, maximum and average predicted WTPs are very similar, suggesting robustness of these parameter estimates. The minimum predicted monthly WTP is €3 for the Czech Republic and the maximum is €12 for Cyprus. The average predicted WTP across all respondents in Model 2 is €7.89, and posterior WTP distributions are strongly positive in all nations.

In terms of policy implications, first and foremost our estimated WTP distributions show that in all 31 nations a positive WTP for EFPT upgrades exist. This suggests an implicit public support for such upgrades at the EU-level. However, the status-quo preservation reaction found in moderate and heavy users suggests that the main barrier to EFPT upgrades may be a political one based on public perceptions. This implication is upheld by our results showing a strong positive effect on WTP from satisfaction with the local transit system. This indicates that EFPT topics may benefit from analysis through the lens of social acceptance, rather than only cost-benefit welfare analysis, similarly to other aspects of the energy transition.[11] As such, concerns of procedural justice and co-creation of the future EFPT system become salient to the transport policy discussion. Stressing local benefits, such as employment opportunities and air quality improvements, are shown by the results as promising ways to build acceptance for EFPT upgrades.

To further relate estimated WTP to the potential benefits of EFPT, we compare local air pollution levels to WTP expressed in percent of median national income in Figure 5. This reveals a clear positive relationship that we interpret as an approximation of the marginal damages curve from air pollution across Europe. These results emphasize that

[11] For instance, additions to energy infrastructure (Cohen et al., 2016a), and system-level change (Azarova et al., 2019)

EFPT upgrades would have stronger positive welfare effects (per capita) in areas currently afflicted with poor air quality across Europe, and thus likely be met with more public support. A tax payment vehicle appears to be a reasonable way for regions to absorb the cost of EFPT investments, as we find few protest responses in our data. The levied taxes can take the mean, lower bound and upper bound of predicted WTP from this analysis as reference points.

In addition to the confounding problem of local transit fares discussed above, there are some caveats related to our study. First, our survey did not specify an exact reduction in air pollutants or GHG emissions that can be expected with the introduction of EFPT, and thus we cannot interpret the findings strictly as WTP for cleaner air; though many of our results point to ambient improvement as a major driver of observed WTP. Second, the specific upgrades to the transit fleet in each area are left vague in the CVM question. Thus, WTP is technology-independent, but may be related to respondents' perceptions of feasible technologies. We attempt to account for these perceptions with spatial data on transit types, and the respondents' perceptions of the environmental performance of their current transit fleet, but some specificity is likely lost. These shortcomings are the cost of a broad-based valuation over a large and heterogeneous geographic area. Future work can take our WTP estimates and findings as a reference for more targeted valuation exercises.

References

Aebischer, B., Catenazzi, G., Jakob, M., 2007. Impact of climate change on thermal comfort, heating and cooling energy demand in Europe, in: Proceedings ECEEE, pp. 859–870.

Andrews, D.F., Mallows, C.L., 1974. Scale mixtures of normal distributions. Journal of the Royal Statistical Society: Series B (Methodological) 36, 99–102.

Attari, S.Z., DeKay, M.L., Davidson, C.I., De Bruin, W.B., 2010. Public perceptions of energy consumption and savings. Proceedings of the National Academy of Sciences 107, 16054–16059.

Azarova, V., Cohen, J., Friedl, C., Reichl, J., 2019. Designing local renewable energy communities to increase social acceptance: Evidence from a choice experiment in Austria, Germany, Italy, and Switzerland. Energy Policy 132, 1176 – 1183.

Bateman, I.J., Carson, R.T., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Pearce, D.W., et al., 2002. Economic valuation with stated preference techniques: A manual. Edward Elgar Publishing Ltd .

Bateman, I.J., Langford, I.H., Jones, A.P., Kerr, G.N., 2001. Bound and path effects in double and triple bounded dichotomous choice contingent valuation. Resource and Energy Economics 23, 191–213.

Beaudoin, J., Farzin, Y.H., Lawell], C.Y.C.L., 2015. Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. Research in Transportation Economics 52, 15 – 22. Sustainable Transportation.

Beaudoin, J., Lawell, C., 2018. The effects of public transit supply on the demand for automobile travel. Journal of Environmental Economics and Management 88, 447 – 467.

Blázquez, L., Boogen, N., Filippini, M., 2013. Residential electricity demand in Spain: New empirical evidence using aggregate data. Energy Economics 36, 648–657.

Büyükalaca, O., Bulut, H., Yılmaz, T., 2001. Analysis of variable-base heating and cooling degree-days for Turkey. Applied Energy 69, 269–283.

Capros, P., De Vita, A., Tasios, N., Siskos, P., Kannavou, M., Petropoulos, A., Evangelopoulou, S., Zampara, M., Papadopoulos, D., Nakos, C., et al., 2016. The EU reference scenario 2016-energy, transport and GHG emissions trends to 2050. .

Chakrabarti, S., 2017. How can public transit get people out of their cars? an analysis of transit mode choice for commute trips in Los Angeles. Transport Policy 54, 80 – 89.

Chen, H., Kwong, J.C., Copes, R., Tu, K., Villeneuve, P.J., Van Donkelaar, A., Hystad, P., Martin, R.V., Murray, B.J., Jessiman, B., et al., 2017. Living near major roads and the incidence of dementia, parkinson's disease, and multiple sclerosis: a population-based cohort study. The Lancet 389, 718–726.

Claudy, M.C., Michelsen, C., O'Driscoll, A., 2011. The diffusion of microgeneration technologies–assessing the influence of perceived product characteristics on home owners' willingness to pay. Energy Policy 39, 1459–1469.

Cohen, J., Moeltner, K., Schmidthaler, M., Reichl, J., 2016a. An empirical analysis of local opposition to new transmission lines across the EU-27. The Energy Journal 37, 59–82.

Cohen, J.J., Moeltner, K., Reichl, J., Schmidthaler, M., 2016b. Linking the value of energy reliability to the acceptance of energy infrastructure: Evidence from the EU. Resource and Energy Economics 45, 124–143.

Cooper, J.C., Hanemann, M., Signorello, G., 2002. One-and-one-half-bound dichotomous choice contingent valuation. Review of Economics and Statistics 84, 742–750.

Devroye, L., 1986. Non-uniform random variate generation. New York: Springer .

EC, 2013. Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions together towards competitive and resource-efficient urban mobility. Technical Report. European Commission.

EC, 2016. European clean bus deployment initiative. Web.

EU, 2016. Mobility and Transport: Electrified railway lines. database. UIC Synopsis, IRG-Rail reports, national sources and estimates (BE, IE).

EU, 2019. Directive (EU) 2019/1161 of the European Parliament and of the Council of 20 June 2019 amending Directive 2009/33/EC on the promotion of clean and energy-efficient road transport vehicles. legislation. European Parliament.

European Commission, 2019. Statistical Pocketbook 2019 - EU Mobility. Publication office of the EU, Luxembourg.

Eurostat, 2010. Statistics on living conditions: Algorithms to compute Social Inclusion Indicators based on EU-SILC and adopted under the Open Method of Coordination. techreport. European Commission.

Fontaras, G., Zacharof, N.G., Ciuffo, B., 2017. Fuel consumption and CO_2 emissions from passenger cars in Europe–laboratory versus real-world emissions. Progress in Energy and Combustion Science 60, 97–131.

Galvis, B., Bergin, M., Boylan, J., Huang, Y., Bergin, M., Russell, A.G., 2015. Air quality impacts and health-benefit valuation of a low-emission technology for rail yard locomotives in Atlanta Georgia. Science of The Total Environment 533, 156 – 164.

Guo, Y., Zeng, H., Zheng, R., Li, S., Barnett, A.G., Zhang, S., Zou, X., Huxley, R., Chen, W., Williams, G., 2016. The association between lung cancer incidence and ambient air pollution in China: a spatiotemporal analysis. Environmental Research 144, 60–65.

Haghshenas, H., Vaziri, M., 2012. Urban sustainable transportation indicators for global comparison. Ecological Indicators 15, 115–121.

Hanemann, M., Loomis, J., Kanninen, B., 1991. Statistical efficiency of double-bounded dichotomous choice contingent valuation. American Journal of Agricultural Economics 73, 1255–1263.

Hanemann, W.M., 1984. Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses. American Journal of Agricultural Economics 66, 332–341.

Hao, H., Geng, Y., Sarkis, J., 2016. Carbon footprint of global passenger cars: Scenarios through 2050. Energy 101, 121–131.

Haraldsson, K., Folkesson, A., Saxe, M., Alvfors, P., 2006. A first report on the attitude towards hydrogen fuel cell buses in Stockholm. International Journal of Hydrogen Energy 31, 317–325.

Harrison, R.M., Deacon, A.R., Jones, M.R., Appleby, R.S., 1997. Sources and processes affecting concentrations of PM_{10} and $PM_{2.5}$ particulate matter in Birmingham (UK). Atmospheric Environment 31, 4103–4117.

Hensher, D.A., 2008. Climate change, enhanced greenhouse gas emissions and passenger transport–what can we do to make a difference? Transportation Research Part D: Transport and Environment 13, 95–111.

Heo, J.Y., Yoo, S.H., 2013. The public's value of hydrogen fuel cell buses: A contingent valuation study. International Journal of Hydrogen Energy 38, 4232–4240.

Holmes, C.C., Held, L., et al., 2006. Bayesian auxiliary variable models for binary and multinomial regression. Bayesian analysis 1, 145–168.

Jerrett, M., Burnett, R.T., Beckerman, B.S., Turner, M.C., Krewski, D., Thurston, G., Martin, R.V., van Donkelaar, A., Hughes, E., Shi, Y., et al., 2013. Spatial analysis of air pollution and mortality in California. American Journal of Respiratory and Critical Care Medicine 188, 593–599.

Karlström, M., 2005. Local environmental benefits of fuel cell buses—a case study. Journal of Cleaner Production 13, 679–685.

Langsdorf, S., 2011. EU energy policy: from the ECSC to the energy roadmap 2050. Green European Foundation .

Lee, D.Y., Elgowainy, A., Vijayagopal, R., 2019. Well-to-wheel environmental implications of fuel economy targets for hydrogen fuel cell electric buses in the United States. Energy Policy 128, 565–583.

Lim, S.Y., Kim, H.J., Yoo, S.H., 2017. Public's willingness to pay a premium for bioethanol in Korea: A contingent valuation study. Energy Policy 101, 20–27.

Lin, B., Tan, R., 2017. Are people willing to pay more for new energy bus fares? Energy 130, 365–372.

Linnerud, K., Toney, P., Simonsen, M., Holden, E., 2019. Does change in ownership affect community attitudes toward renewable energy projects? Evidence of a status quo bias. Energy Policy 131, 1–8.

Liu, C., Shen, Q., 2011. An empirical analysis of the influence of urban form on household travel and energy consumption. Computers, Environment and Urban Systems 35, 347–357.

Liu, Y., 2014. Household demand and willingness to pay for hybrid vehicles. Energy Economics 44, 191–197.

McLeod, D.M., Bergland, O., 1999. Willingness-to-Pay Estimates Using the Double-Bounded Dichotomous-Choice Contingent Valuation Format: A Test for Validity and Precision in a Bayesian Framework. Land Economics 75, 115–125.

Neves, T., Mourato, S., 2004. Comparative analysis of Berlin, London, Luxembourg and Perth ex-ante surveys.

Noel, L., Carrone, A.P., Jensen, A.F., de Rubens, G.Z., Kester, J., Sovacool, B.K., 2019. Willingness to pay for electric vehicles and vehicle-to-grid applications: A Nodic choice experiment. Energy Economics 78, 525–534.

O'Garra, T., Mourato, S., Garrity, L., Schmidt, P., Beerenwinkel, A., Altmann, M., Hart, D., Graesel, C., Whitehouse, S., 2007. Is the public willing to pay for hydrogen buses? A comparative study of preferences in four cities. Energy Policy 35, 3630–3642.

O'Garra, T., Mourato, S., 2007. Public preferences for hydrogen buses: comparing interval data, OLS and quantile regression approaches. Environmental and Resource Economics 36, 389–411.

O'Garra, T., Mourato, S., Garrity, L., Schmidt, P., Beerenwinkel, A., Altmann, M., Hart, D., Graesel, C., Whitehouse, S., 2007. Is the public willing to pay for hydrogen buses? A comparative study of preferences in four cities. Energy Policy 35, 3630–3642.

Peters, J., Wainwright, S., 2017. Clean power for transport infrastructure deployment. report. Directorate-General for Mobility and Transport.

Phaneuf, D.J., Requate, T., 2016. A course in environmental economics: theory, policy, and practice. Cambridge University Press.

Poder, T.G., He, J., 2017. Willingness to pay for a cleaner car: The case of car pollution in Quebec and France. Energy 130, 48–54.

Rahmani, D., Loureiro, M.L., 2019. Assessing drivers' preferences for hybrid electric vehicles (HEV) in Spain. Research in Transportation Economics 73, 89–97.

Reichl, J., Cohen, J., Kollmann, A., Azarova, V., Klöckner, C., Royrvik, J., Vesely, S., Carrus, G., Panno, A., Tiberio, L., Fritsche, I., Masson, T., Chokrai, P., Lettmayer, G., Schwarzinger, S., Bird, N., 2019. International survey of the echoes project. Zenodo 1.0.0.

Rivers, N., Plumptre, B., 2018. The effectiveness of public transit tax credits on commuting behaviour and the environment: Evidence from Canada. Case Studies on Transport Policy 6, 651 – 662.

Saxe, M., Folkesson, A., Alvfors, P., 2007. A follow-up and conclusive report on the attitude towards hydrogen fuel cell buses in the CUTE project—from passengers in Stockholm to bus operators in Europe. International Journal of Hydrogen Energy 32, 4295–4305.

Spiller, E., Stephens, H., Timmins, C., Smith, A., 2014. The effect of gasoline taxes and public transit investments on driving patterns. Environmental and Resource Economics 63, 633–657.

Tan, R., Lin, B., 2019. Public perception of new energy vehicles: Evidence from willingness to pay for new energy bus fares in China. Energy Policy 130, 347–354.

Terzi, E., Argyropoulos, G., Bougatioti, A., Mihalopoulos, N., Nikolaou, K., Samara, C., 2010. Chemical composition and mass closure of ambient PM_{10} at urban sites. Atmospheric Environment 44, 2231–2239.

UITP, 2015. Bus Systems in Europe : towards a higher quality of urban life and a reduction of pollutants and CO_2 emissions. position paper. International Association of Public Transport.

Wall, G., Felstead, T., Richards, A., McDonald, M., 2008. Cleaner vehicle buses in Winchester. Transport Policy 15, 55–68.

Weichenthal, S., Hatzopoulou, M., Goldberg, M.S., 2014. Exposure to traffic-related air pollution during physical activity and acute changes in blood pressure, autonomic and micro-vascular function in women: a cross-over study. Particle and Fibre Toxicology 11, 70.

Wesselink, B., Harmsen, R., Wolfgang, E., 2010. Energy savings 2020: How to triple the impact of energy saving policies in Europe-a contributing study to roadmap 2050. ECF–European Climate Foundation, Berlin .

Willis, K., Scarpa, R., Gilroy, R., Hamza, N., 2011. Renewable energy adoption in an ageing population: Heterogeneity in preferences for micro-generation technology adoption. Energy Policy 39, 6021–6029.

Yan, X., Levine, J., Zhao, X., 2019. Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data. Transportation Research Part C: Emerging Technologies 105, 683 – 696.

Table 1: The contingent valuation question for EFPT

Explanations	Imagine that the current fleet of public transportation vehicles in your area will be upgraded to be more environmentally friendly. The new vehicles will decrease air pollution within your area and will lower the carbon emissions from the public transportation sector. However, the new vehicles will be more costly to run. Therefore, local politicians ask all residents in the area in a referendum whether this change to environmentally friendly vehicles shall take place.	
Questions	How would you vote on the referendum if you would requited to pay [randomly assign a national bid price] more per month in taxes? You would have to pay this fee even if you never use public transport.	
Choice	I would vote "YES" to support the new public transportation system	I would vote "No" and not support the new public transportation system

Table 2: Percentage of respondents accepting the bid by bid value and country

country	Number of respondents	Number of protests	% of protest	% yes 1	% yes 2	% yes 3	% yes 4	% yes 5	% yes 6
Austria	263	2	0.75%	100.00%	67.65%	51.02%	43.48%	23.53%	17.78%
Belgium	293	6	2.01%	100.00%	50.00%	43.64%	50.98%	33.33%	12.50%
Bulgaria	174	1	0.57%	100.00%	78.38%	92.86%	34.48%	26.67%	13.79%
Croatia	278	1	0.36%	100.00%	70.59%	61.90%	36.36%	20.45%	20.00%
Cyprus	92	3	3.16%	100.00%	92.31%	86.67%	62.50%	13.33%	33.33%
Czech Republic	298	2	0.67%	100.00%	42.31%	34.04%	32.20%	12.77%	16.98%
Denmark	222	4	1.77%	100.00%	47.06%	56.76%	41.46%	17.39%	16.67%
Estonia	145	4	2.68%	100.00%	71.43%	55.56%	45.71%	5.00%	30.00%
Finland	208	3	1.42%	100.00%	59.52%	56.25%	41.30%	10.81%	18.75%
France	256	4	1.54%	100.00%	53.19%	53.49%	50.00%	13.64%	17.07%
Germany	256	3	1.16%	100.00%	50.00%	34.88%	37.50%	15.22%	16.22%
Greece	83	3	3.49%	100.00%	83.33%	38.46%	10.00%	20.00%	17.65%
Hungary	209	0	0.00%	100.00%	73.08%	56.67%	41.67%	35.29%	26.47%
Ireland	197	1	0.51%	100.00%	71.43%	69.23%	62.50%	17.65%	34.62%
Italy	226	1	0.44%	100.00%	67.44%	43.75%	43.90%	26.67%	17.65%
Latvia	204	6	2.86%	100.00%	57.50%	40.00%	19.35%	10.53%	9.09%
Lithuania	257	7	2.65%	100.00%	44.44%	51.06%	52.50%	30.00%	18.37%
Luxembourg	275	4	1.43%	100.00%	81.82%	60.47%	48.00%	28.00%	20.00%
Malta	121	1	0.82%	100.00%	61.90%	63.16%	40.63%	15.00%	0.00%
Norway	220	5	2.22%	100.00%	66.67%	53.33%	44.00%	15.56%	5.88%
Poland	265	6	2.21%	100.00%	67.39%	38.64%	40.91%	27.45%	27.78%
Portugal	158	0	0.00%	100.00%	61.11%	61.54%	41.67%	19.35%	25.00%
Romania	67	1	1.47%	100.00%	55.56%	57.14%	90.00%	7.69%	42.86%
Slovakia	226	7	3.00%	100.00%	53.33%	46.88%	38.89%	21.05%	23.40%
Slovenia	214	8	3.60%	100.00%	57.14%	42.50%	50.00%	12.50%	27.03%
Spain	230	0	0.00%	100.00%	59.46%	42.50%	31.37%	23.53%	22.22%
Sweden	165	3	1.79%	100.00%	70.21%	48.39%	34.48%	24.14%	-
Switzerland	276	7	2.47%	100.00%	72.50%	36.00%	53.49%	19.15%	20.75%
The Netherlands	267	14	4.98%	100.00%	63.83%	48.78%	50.00%	23.40%	18.18%
Turkey	272	4	1.45%	100.00%	63.64%	55.17%	42.22%	37.29%	40.91%
United Kingdom	103	1	0.96%	100.00%	63.16%	68.18%	31.58%	20.00%	50.00%
average			1.72%	100.00%	62.35%	51.35%	42.97%	21.75%	20.94%

Bid values include €0, €2, €4, €15 and €20.
Bid values were shown to respondents in equivalent values of local currency where applicable.

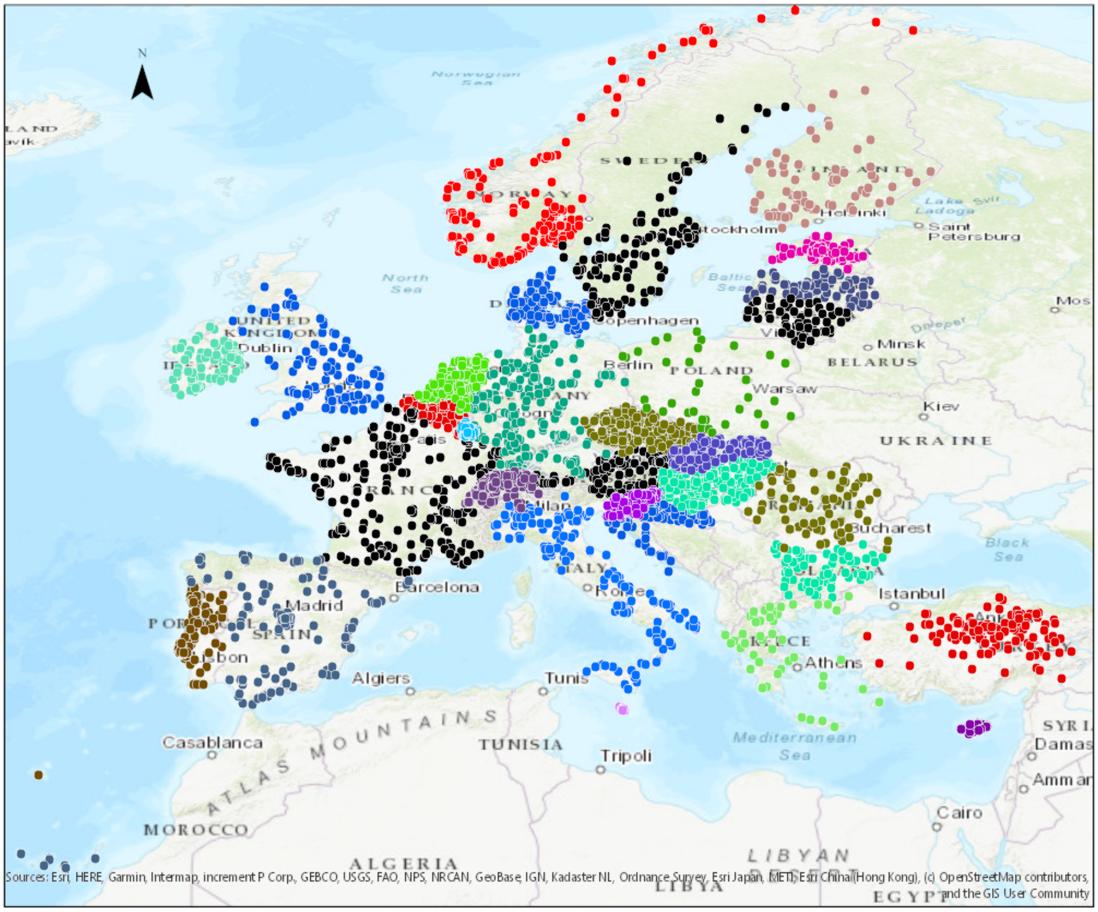

Figure 1: The spatial distribution of respondents

Table 3: Variable definitions

category	variables	Definitions
	constant	constant term
	ele_mean5km	elevation mean in 5km buffer
	trans_densIndex	transportation density index
	landcover_percent5km	the urban landcover percentage in 5km buffer
location-specific variables	total_CDD	annual sum of CDD
	total_HDD	annual sum of HDD
	annual_prep	annual average of prep
	PM10_Jan	monthly PM10
	PM10_Jul	monthly PM10
	cc_nottrue	=1 if the person does not really believe that CC is happening
	ren_jobs_yes	=1 if the person believes renewable energy create jobs
	ren_env_yes	=1 if person believes renewable energy will benefit the environment
Attitudes variables	cc_cause_man	=1 if person believes CC is mostly anthropogenic
	environ_pro	=1 if the person is self-reported pro environmental
	transit_satisfied	=1 if respondent is satisfied with current public transport
	transit_environment	=1 if respondent considers current public is environmentally friendly
	transit_trips	How many trips do respondents take per week using public transportation on average?
	total_min	total minutes of public transportation
	child	=1 if the respondent has at least one child
	employed	=1 if person is full-time or part-time employed
	young_age	=1 if respondent is age (18-34)
	mid_age	=1 if respondent is age (35-54)
	old_age	=1 if respondent is age (>55)
	basic_edu	=1 if respondent has elementary or secondary education
	profession_edu	=1 if respondent has profession or practical education
	high_edu	=1 if respondent has qualification or university education
Socio-demographic variables	residence_less5	=1 if respondent has lived at current address less than 5yrs
	residence_less10	=1 if respondent has lived at current address 5-10yrs
	residence_less20	=1 if respondent has lived at current address 10-20yrs
	residence_more20	=1 if respondent has lived at current address more than 20yrs
	non_users	=1 if respondent is public transport non-user (rarely use)
	occasional_users	=1 if respondent is public transport occasional user (1-4 trips per week)
	moderate_users	=1 if respondent is public transport moderate user (5-8 trips per week)
	heavy_users	=1 if respondent is public transport heavy user (over 9 trips per week)
	inc_equ	the total net income per household member EUR/month
country dummy variables	dum_AT	country dummy for baseline (omitted) country
	dum_BE-dum_UK	country dummy for each of 30 countries

CC indicates climate change.
Austria is taken as the baseline (omitted) country.

Table 4: Percentages of categories for socio-demographic variables

variable	categories	percent of the sample (%)
gender	male=1	49.57
	female=0	50.4
	other=2	0.03
age	18-34	34.34
	35-44	23.07
	45-54	20.05
	over 55	22.55
household size	1	16.23
	2	31.15
	3	23.93
	4	19.63
	5	6.55
	over 5	2.52
employment	paid employment (30hrs a week or more)	54.62
	paid employment (less than 30hrs a week)	7.58
	self-employed	6.49
	retired/pensioned	12.9
	stay-home without payment	3.9
	full-time student	5.48
	unemployed	5.86
	other	2.91
education	elementary or secondary school	11.44
	professional training (practical skills)	17.96
	A-level (qualification for university)	22.79
	university or college degree	45.86
	other	1.95
years in area	5 years or less	28.44
	5-10 years	17.53
	10-20 years	21.04
	more than 20 years	32.99
children	0	38.85
	1	22.55
	2	27.58
	3	8.39
	4	1.83
	5	0.57
	over 5	0.25
monthly income	monthly income<=€500	24.29
	€500<monthly income<=€900	25.75
	€900<monthly income<=€1800	24.22
	€1800<monthly income<=€3000	18.62
	monthly income>€3000 euros	6.8

$N = 6,520$

Table 5: Percentages of categories for attitudes variables

variable	categories	percent of the sample (%)
transit_satisfied	very dissatisfied	9.66
	dissatisfied	19.57
	neither satisfied nor dissatisfied	31.18
	satisfied	31.04
	very satisfied	8.54
transit_environment	strongly disagree	9.86
	disagree	28.5
	agree nor disagree	37.45
	agree	22.02
	Strongly agree	2.16
transit_trips	0 trips	58.4
	1-4 trips	19.16
	5-8 trips	9.1
	9-12 trips	7.64
	more than 12 trips	5.71
cc_nottrue	0	94.23
	1	5.77
cc_cause_man	0	44.86
	1	55.14
ren_jobs_yes	0	44.22
	1	55.78
ren_env_yes	0	16.76
	1	83.24
environ_pro	0	35.89
	1	64.11

$N = 6,520$
Definitions of all variables are given in table 3.

Table 6: Summary statistics for continuous variables

Variable	Mean	median	Std	Min	Max
PM10_Jan	35.52	29.03	20.46	4.72	145.75
PM10_Jul	16.54	15.35	6.57	3.22	44.61
total_HDD	66.63	63.65	25.27	0.00	182.76
total_CDD	1.29	0.00	2.50	0.00	16.27
annual_prep	1.87	1.67	0.75	0.25	8.35
ele_mean5km	252.03	126.96	313.58	-10.00	2273.22
trans_densIndex	0.14	0.04	0.28	0.00	2.13
landcover_percent5km	0.25	0.17	0.23	0.00	0.91
total_min	17.58	0.00	28.67	0.00	230.50
inc_equ	1278.59	900.00	1048.30	6.50	8180.30

$N = 6,520$
Definitions of all variables are given in table 3.

Table 7: Estimation results of Model 1 and Model 2

	Model 1			Model 2		
variables	mean	std	p>0	mean	std	p>0
constant	0.229	2.457	0.538	1.021	2.772	0.645
ele_mean5km	0.000	0.001	0.522	0.001	0.001	0.687
trans_densIndex	-1.185	1.329	0.186	-0.495	1.599	0.379
landcover_percent5km	-1.927	1.487	0.097	-2.588	1.703	0.064
total_CDD	-0.066	0.150	0.329	-0.002	0.172	0.495
total_HDD	0.032	0.025	0.904	0.013	0.027	0.678
annual_prep	-0.169	0.402	0.337	-0.232	0.459	0.307
PM10_Jan	-0.006	0.019	0.374	-0.002	0.021	0.456
PM10_Jul	0.063	0.063	0.842	0.062	0.073	0.802
cc_nottrue	-1.279	0.840	0.064	-0.863	0.949	0.181
ren_jobs_yes	2.029	0.421	1.000	2.405	0.479	1.000
ren_env_yes	0.723	0.567	0.899	1.365	0.637	0.984
cc_cause_man	0.062	0.403	0.561	0.331	0.458	0.766
environ_pro	2.495	0.436	1.000	2.660	0.493	1.000
transit_satisfied	0.785	0.425	0.968	0.746	0.491	0.936
transit_environment	-0.058	0.483	0.452	-0.576	0.564	0.153
total_min	0.012	0.009	0.921	0.002	0.012	0.569
child	1.613	0.452	1.000	1.375	0.512	0.997
employed	0.373	0.432	0.807	0.399	0.490	0.792
mid_age	-0.408	0.486	0.200	-0.270	0.562	0.316
old_age	0.534	0.634	0.800	1.396	0.716	0.975
profession_edu	-0.816	0.739	0.134	-0.752	0.814	0.177
high_edu	-0.063	0.641	0.460	-0.203	0.716	0.389
residence_less10	0.900	0.582	0.939	0.288	0.672	0.666
residence_less20	1.119	0.570	0.975	0.506	0.655	0.780
residence_more20	0.319	0.537	0.724	0.026	0.612	0.518
inc_equ	0.001	0.000	0.973	0.001	0.000	0.989
occasional_users	-0.091	0.549	0.435	0.126	0.580	0.586
moderate_users	-1.499	0.752	0.023			
heavy_users	-2.446	0.737	0.000			
scale	6.673	0.209	1.000	scale	6.635	0.235

Model 1 includes all user types, $N = 6,520$; Model 2 includes only occasional and non-users of public transit $N = 5,057$.

Both models include country fixed effects; their estimates are available upon request.

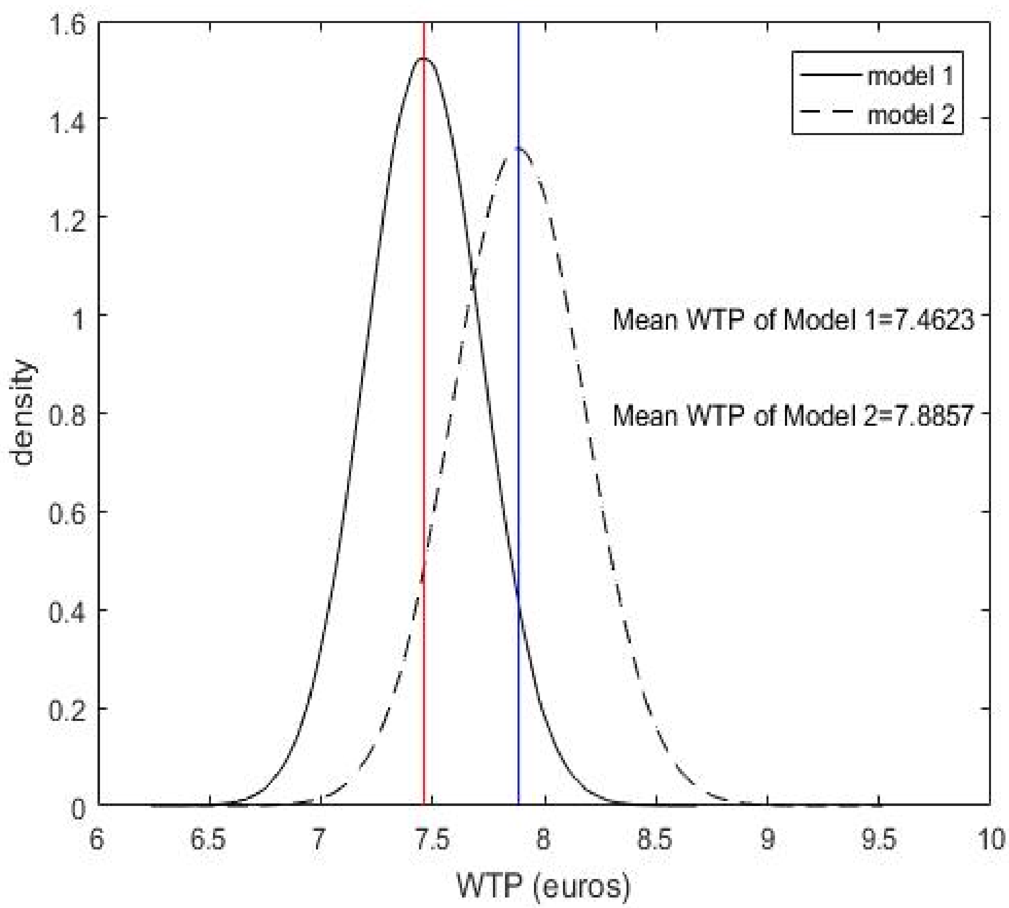

Figure 2: PPD of predicted full WTP for Model 1 and Model 2

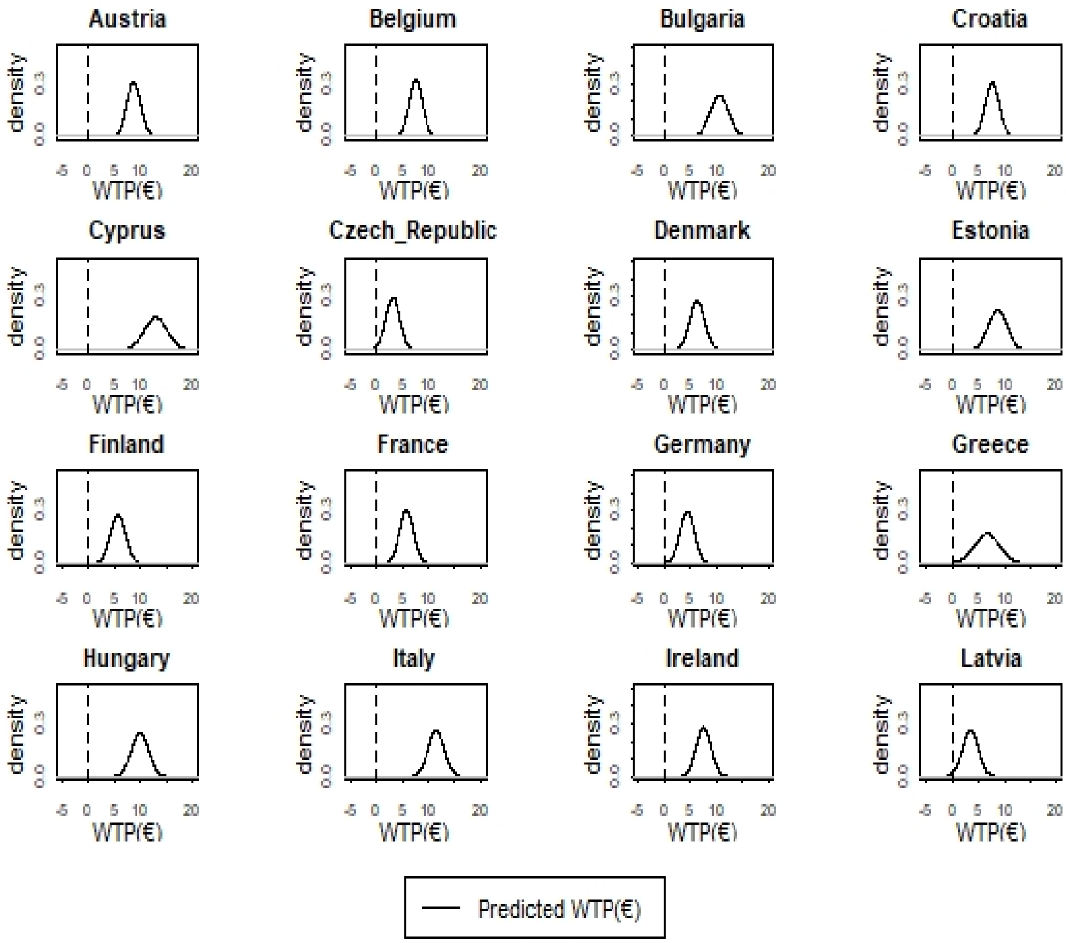

Figure 3: WTP predictions for Model 2

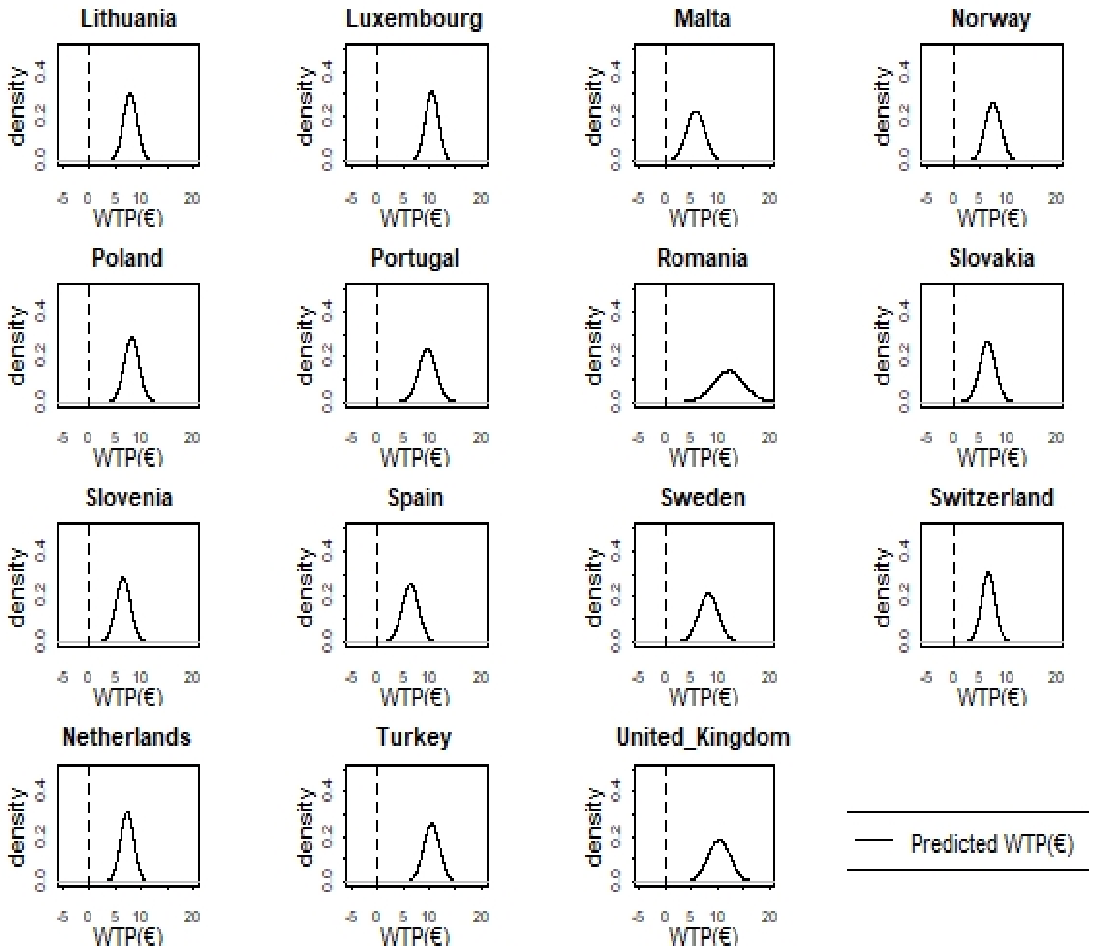

Figure 4: WTP predictions for Model 2, continued

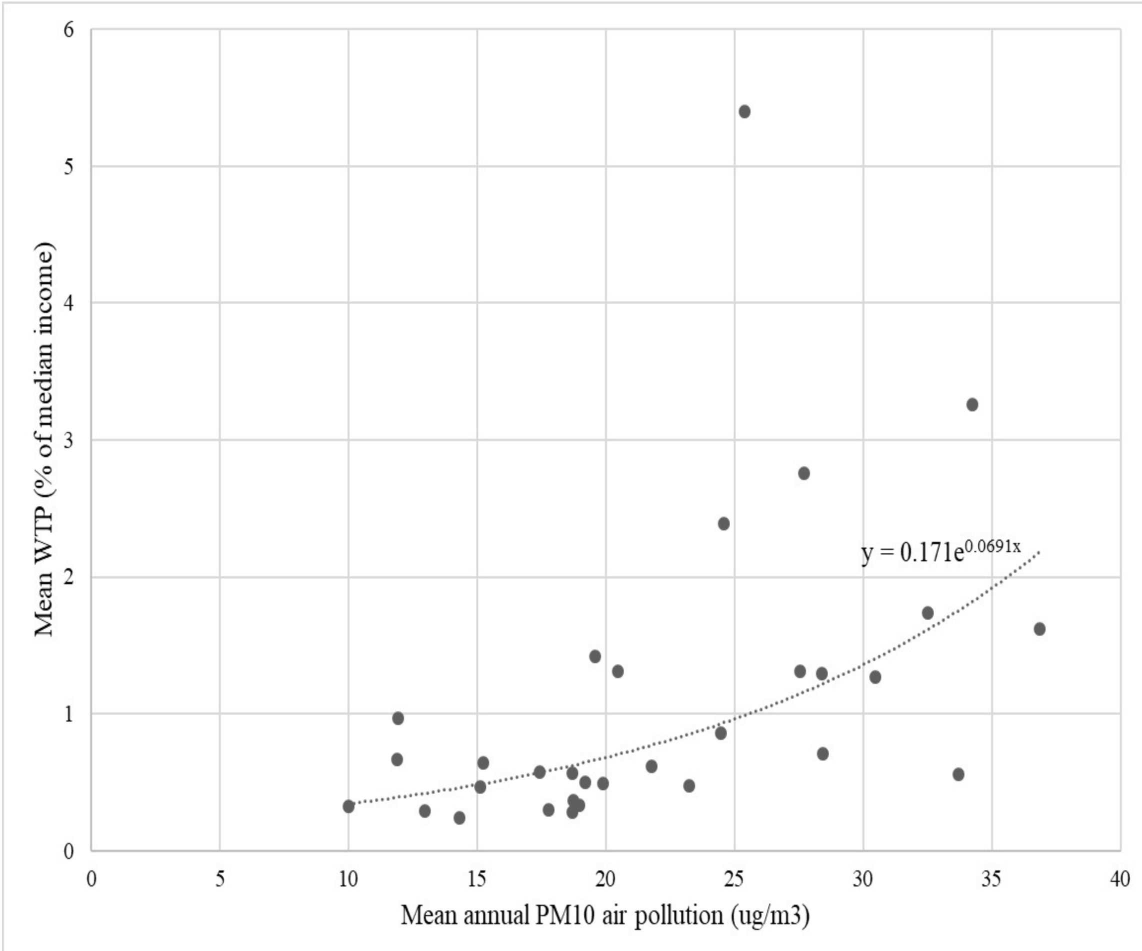

Figure 5: Average country WTP as proportion of median income and PM_{10} concentration averaged over months for Model 2

Appendix

Detailed steps of the GS

A fully efficient conditioned GS proceeds by sequentially drawing from $p\left(\boldsymbol{\beta}|s^2,\mathbf{y}^*,\boldsymbol{\lambda}\right)$, $p(y^*|s^2,\boldsymbol{\beta},\boldsymbol{\lambda},\mathbf{y})$ and $p(\boldsymbol{\lambda}|s^2,\boldsymbol{\beta},\mathbf{y}^*)$ followed by a draw from $p\left(s^2|\boldsymbol{\beta},\mathbf{y}^*,\boldsymbol{\lambda}\right)$, and a joint draw of $\mathbf{y}^*$ and $\boldsymbol{\lambda}$ via

$$p(\mathbf{y}^*,\boldsymbol{\lambda}|\boldsymbol{\beta},s^2,\mathbf{y}) = p(y^*|\boldsymbol{\beta},s^2,\mathbf{y})p(\boldsymbol{\lambda}|\boldsymbol{\beta},s^2,\mathbf{y}^*) \tag{9}$$

The specifics for these individual steps are as follows.

$$\begin{aligned}
&\boldsymbol{\beta}|s^2,\mathbf{y}^*,\boldsymbol{\lambda} \sim n(\mu_1,\mathbf{V}_1) \quad \text{with} \\
&\mathbf{V}_1 = \left(\mathbf{V}_0^{-1} + \mathbf{X}'(s^2\boldsymbol{\Lambda})^{-1}\mathbf{X}\right) \\
&\mu_1 = \mathbf{V}_1\left(\mathbf{V}_0^{-1}\mu_0 + \mathbf{X}'(s^2\boldsymbol{\Lambda})^{-1}\mathbf{y}^*\right)
\end{aligned} \tag{10}$$

That is, conditional on the variance terms, the latent data and the scale parameter the coefficient vector follows the typical normal conditional posterior, with the moments a function of prior parameters and data. Conditional on the coefficient vector, the latent data and variance terms, scale parameter s^2 follows a inverse-gamma conditional posterior, with the shape and scale parameter a function of prior parameters and data.

$$\begin{aligned}
&s^2|\boldsymbol{\beta},\mathbf{y}^*,\boldsymbol{\lambda} \sim ig(\nu_1,\tau_1) \quad \text{with} \\
&\nu_1 = \frac{2\nu_0 + n}{2} \\
&\tau_1 = \nu_0 + \frac{1}{2}(\mathbf{y}^* - \mathbf{X}\boldsymbol{\beta})'\boldsymbol{\Lambda}^{-1}(\mathbf{y}^* - \mathbf{X}\boldsymbol{\beta})
\end{aligned} \tag{11}$$

Draws of the latent outcomes y^* are taken individually for each observation, and follow a truncated standard logistic, with upper or lower truncation bounds given by b_i, depending on the response.

$$\begin{aligned}
&y_i^* \sim logistic(\mathbf{x}_i'\boldsymbol{\beta},s)I(y_i^* > b_i) \quad \text{if} \quad y_i = 1 \\
&y_i^* \sim logistic(\mathbf{x}_i'\boldsymbol{\beta},s)I(y_i^* < b_i) \quad \text{if} \quad y_i = 0
\end{aligned} \tag{12}$$

The final step involves individual-specific draws of the variances λ_i, given $\boldsymbol{\beta}$ and $\tilde{\mathbf{y}}_i^*$. As described in Holmes et al. (2006), this is not straightforward, as inversion methods are not known for the KS distribution. Instead, we follow Devroye (1986) and use a rejection sampling approach with Generalized Inverse Gaussian (GIG) proposal density. That is, a given λ_i is drawn from the GIG with parameters 1/2,1, and $r_i^2 =$

$(\tilde{y}_i^* - \tilde{\mathbf{x}}_i'\boldsymbol{\beta})^2$, i.e,

$$q(\lambda_i) \sim \lambda_i^{-1/2} exp\left(-\frac{1}{2}(r_i^2\lambda_i^{-1} + \lambda_i)\right) \tag{13}$$

The acceptance probability $\alpha(\lambda_i)$ is then given by

$$\begin{aligned}
&\alpha(\lambda_i) = \frac{p(\tilde{y}_i^*|\boldsymbol{\beta}, \lambda_i)p(\lambda_i)}{M * q(\lambda_i)} = \\
&\frac{\lambda_i^{-1/2} exp\left(-\frac{1}{2}(r_i^2\lambda_i^{-1})\right) * \frac{1}{4}\lambda_i^{-1/2} KS\left(\frac{1}{2}\lambda_i^{1/2}\right)}{\lambda_i^{-1/2} exp\left(-\frac{1}{2}\left(r_i^2\lambda_i^{-1} + \lambda_i\right)\right)} = \\
&exp(\frac{1}{2}\lambda_i)\frac{1}{4}\lambda_i^{-1/2} KS\left(\frac{1}{2}\lambda_i^{1/2}\right)
\end{aligned} \tag{14}$$

where the scaling constant M can be set to i. The acceptance probability can then be evaluated via an alternating series representation and an efficient set of squeezing functions, as shown in Appendix A4 of Holmes et al. (2006).

Calculations of the HDD and CDD

Heating degree days:

$$HDD_k = \begin{cases} 18 - t_k & \text{if} \quad t_k \leq 15 \\ 0 & \text{if} \quad t_k > 15 \end{cases} \tag{15}$$

Cooling degree days:

$$CDD_k = \begin{cases} t_k - 22 & \text{if} \quad t_k \geq 22 \\ 0 & \text{if} \quad t_k < 22 \end{cases} \tag{16}$$

where t_k is the observed monthly mean temperature for month k. After computing the HDD and CDD for each month, we aggregate these values to obtain the annual sum of HDD and CDD for each respondent.

Sources of location-specific variables

The source of air pollutants is the European Environment Agency (EEA) (`http://discomap.eea.europa.eu/map/fme/AirQualityExport.htm`). We also download the raster of elevation from the EEA (`https://www.eea.europa.eu/data-and-maps/data/world-digital-elevation-model-etopo5`).

The source of precipitation and temperature is the E-OBS which is part of the Copernicus Programme (`https://surfobs.climate.copernicus.eu/dataaccess/access_eobs.php#datafiles`). We classify land-cover as urban based on raster data from the Copernicus Programme (`https://land.copernicus.eu/pan-`

european/corine-land-cover/clc2018?tab=download) where codes 111, 112 and 141 are jointly redefined to denote urban areas.

The source of stations of different transportation modes is from the Geofabrik (http://download.geofabrik.de/europe.html). We download the shapefiles for majority of countries and download the osm file for those without shapefiles. As the osm files are very large, we extract the station information from these osm files using the osmfilter. Then, we use the ArcMap to load the osm file for each transportation mode and then convert them as shapefiles.

Additional figures and tables

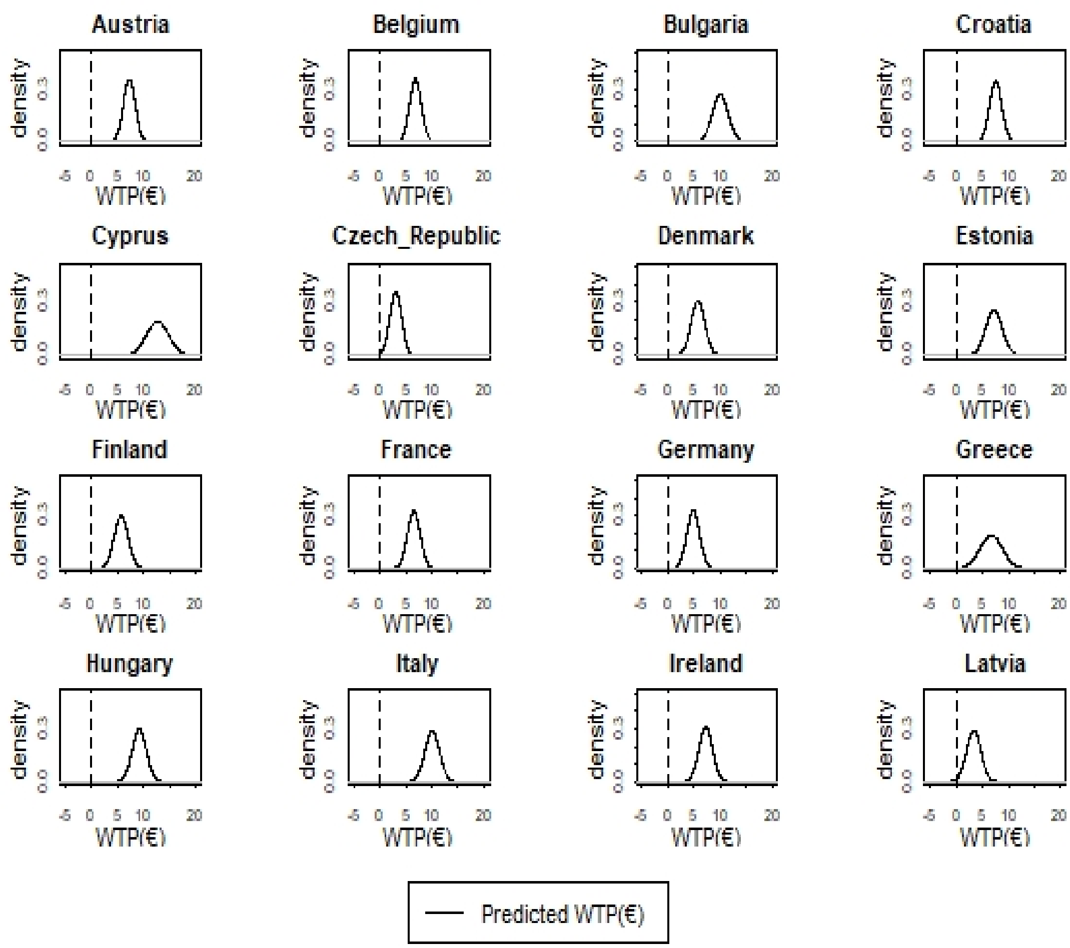

Figure 6: WTP predictions for Model 1

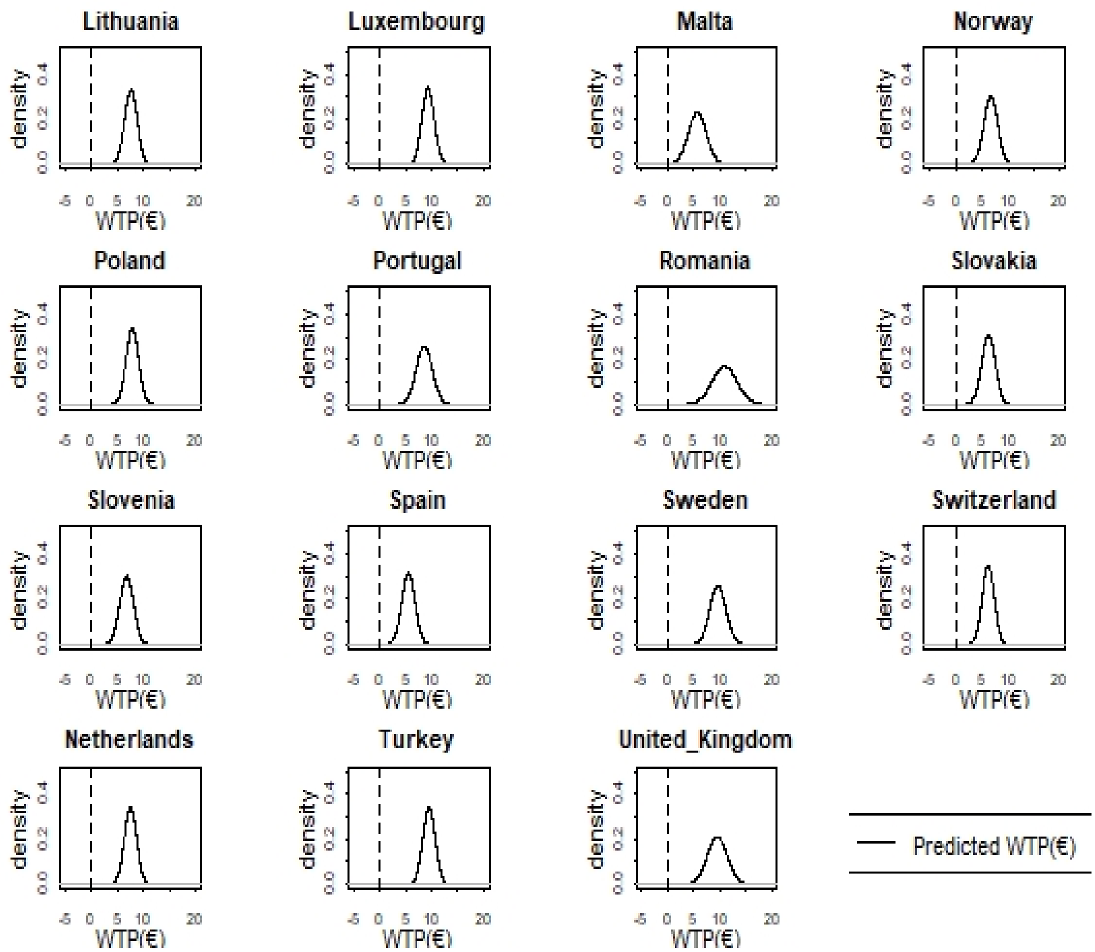

Figure 7: WTP predictions for Model 1, continued

Table 8: Comparison of quota sampling variables to national indicators

	Indicator					
	age		gender		monthly income	
Country	mean age in sample	median age of population	% males in sample	% males of population*	Sample**	population***
Austria	40.48	43.2	0.57	0.49	€ 1,473.01	€ 2,063.00
Belgium	39.61	41.6	0.52	0.49	€ 1,538.46	€ 1,899.00
Bulgaria	40.06	44.2	0.49	0.49	€ 317.86	€ 299.00
Croatia	40.47	43.5	0.53	0.49	€ 469.94	€ 518.00
Cyprus	40.46	38.2	0.51	0.49	€ 1,069.46	€ 1,208.00
Czech Rep.	39.77	42.3	0.50	0.49	€ 661.39	€ 690.00
Denmark	43.42	41.8	0.49	0.49	€ 2,116.24	€ 2,449.00
Estonia	38.11	42.1	0.54	0.49	€ 857.36	€ 782.00
Finland	39.54	42.7	0.48	0.49	€ 1,706.10	€ 1,999.00
France	40.00	41.4	0.51	0.49	€ 1,724.56	€ 1,840.00
Germany	41.65	46	0.50	0.49	€ 1,660.52	€ 1,827.00
Greece	37.26	44.7	0.55	0.49	€ 543.13	€ 633.00
Hungary	39.90	42.6	0.48	0.49	€ 378.70	€ 416.00
Ireland	41.61	37.5	0.50	0.49	€ 1,733.48	€ 1,907.00
Italy	39.68	46.3	0.50	0.49	€ 1,091.53	€ 1,379.00
Latvia	38.29	43.5	0.52	0.49	€ 599.84	€ 551.00
Lithuania	41.14	43.8	0.57	0.49	€ 557.63	€ 511.00
Luxembourg	44.15	39.6	0.51	0.51	€ 3,017.49	€ 3,006.00
Malta	39.52	41.6	0.42	0.51	€ 1,072.63	€ 1,208.00
Norway	39.57	39.5	0.51	0.49	€ 2,733.88	€ 3,206.00
Poland	40.38	40.7	0.52	0.49	€ 504.18	€ 495.00
Portugal	37.68	44.9	0.52	0.49	€ 717.97	€ 756.00
Romania	40.88	42.2	0.55	0.49	€ 200.54	€ 229.00
Slovakia	41.10	40.2	0.49	0.49	€ 499.76	€ 599.00
Slovenia	38.98	43.7	0.51	0.49	€ 741.92	€ 1,059.00
Spain	40.21	43.8	0.44	0.49	€ 1,121.03	€ 1,184.00
Sweden	40.05	40.8	0.47	0.51	€ 1,718.39	€ 1,948.00
Switzerland	44.13	42.5	0.42	0.49	€ 3,041.77	€ 3,688.00
Netherlands	40.16	42.6	0.52	0.49	€ 1,723.62	€ 1,963.00
Turkey	37.75	31.4	0.50	0.51	€ 412.04	€ 313.00
UK	40.49	40	0.50	0.49	€ 1,715.35	€ 1,750.00
Total	40.36	41.9	0.50	0.49	€ 1,278.59	€ 1,367.00

* ratio of women per 100 men
** equivalised mean monthly income using 1st - 4th quartile values and the 90th percentile value (for calculation method see: (Eurostat, 2010))
*** for the purpose of comparing with Eurostat statistics, mean of equivalised monthly income is calculated; equivalised income is net household income per household member following formulas in (Eurostat, 2010)

Table 9: Predicted WTP for Model 1

country	Predict Expected WTP				Predict full WTP			
	tmean	std	low	hi	tmean	std	low	hi
Austria	7.234	0.848	5.543	8.873	7.234	1.129	4.986	9.419
Belgium	6.843	0.873	5.067	8.495	6.843	1.123	4.654	9.068
Bulgaria	10.02	1.179	7.658	12.28	10.02	1.495	7.126	13.01
Croatia	7.551	0.911	5.798	9.375	7.552	1.165	5.255	9.827
Cyprus	12.68	1.661	9.404	15.93	12.69	2.087	8.549	16.74
Czech_Republic	3.07	0.875	1.348	4.785	3.071	1.122	0.803	5.207
Denmark	5.743	1.001	3.775	7.709	5.744	1.29	3.144	8.209
Estonia	7.228	1.224	4.838	9.642	7.226	1.584	4.033	10.26
Finland	5.688	1.043	3.571	7.673	5.689	1.34	3.021	8.28
France	6.521	0.955	4.632	8.38	6.521	1.218	4.055	8.849
Germany	4.825	0.941	2.939	6.634	4.823	1.208	2.442	7.186
Greece	6.697	1.673	3.385	9.951	6.696	2.136	2.49	10.86
Hungary	9.153	1.048	7.089	11.21	9.153	1.341	6.498	11.76
Italy	10.06	1.093	7.856	12.15	10.06	1.392	7.256	12.72
Ireland	7.245	1.009	5.261	9.222	7.244	1.292	4.63	9.712
Latvia	3.333	1.085	1.158	5.423	3.335	1.377	0.585	5.991
Lithuania	7.563	0.952	5.687	9.431	7.563	1.215	5.187	9.957
Luxembourg	9.295	0.926	7.486	11.12	9.295	1.179	6.966	11.59
Malta	5.686	1.339	3.135	8.395	5.685	1.734	2.179	8.996
Norway	6.712	1.043	4.696	8.789	6.712	1.325	4.082	9.279
Poland	7.831	0.926	5.963	9.603	7.831	1.188	5.412	10.08
Portugal	8.568	1.206	6.187	10.92	8.568	1.543	5.492	11.55
Romania	10.92	1.858	7.23	14.52	10.92	2.375	6.354	15.67
Slovakia	6.262	1.013	4.218	8.192	6.262	1.293	3.643	8.725
Slovenia	6.749	1.027	4.693	8.727	6.748	1.319	4.095	9.279
Spain	5.526	0.993	3.552	7.447	5.526	1.273	2.941	7.944
Sweden	9.629	1.206	7.237	11.97	9.629	1.531	6.584	12.6
Switzerland	6.205	0.891	4.462	7.955	6.205	1.15	3.956	8.476
Netherlands	7.49	0.924	5.682	9.311	7.489	1.185	5.086	9.75
Turkey	9.497	0.917	7.656	11.26	9.495	1.175	7.153	11.76
United_Kingdom	9.515	1.493	6.529	12.39	9.513	1.912	5.819	13.34

Table 10: Predicted WTP for Model 2

country	Predict Expected WTP				Predict full WTP			
	tmean	std	low	hi	tmean	std	low	hi
Austria	8.7	0.962	6.764	10.544	8.699	1.298	6.074	11.171
Belgium	7.579	0.974	5.625	9.447	7.579	1.248	5.081	9.978
Bulgaria	10.551	1.351	7.868	13.174	10.551	1.707	7.195	13.901
Croatia	7.67	1.032	5.608	9.663	7.671	1.317	5.114	10.278
Cyprus	12.923	1.743	9.475	16.324	12.925	2.187	8.551	17.144
Czech_Republic	3.123	1.055	1.05	5.188	3.124	1.352	0.394	5.704
Denmark	6.293	1.122	4.041	8.448	6.293	1.441	3.427	9.086
Estonia	8.706	1.392	5.947	11.406	8.708	1.791	5.109	12.148
Finland	5.653	1.124	3.439	7.851	5.654	1.443	2.799	8.461
France	5.769	1.037	3.69	7.76	5.768	1.326	3.084	8.291
Germany	4.375	1.058	2.212	6.376	4.376	1.357	1.711	7.039
Greece	6.651	1.887	2.979	10.394	6.65	2.401	1.739	11.194
Hungary	9.9	1.293	7.345	12.425	9.9	1.648	6.571	13.051
Italy	11.468	1.206	9.061	13.796	11.468	1.527	8.403	14.402
Ireland	7.529	1.12	5.295	9.693	7.528	1.43	4.71	10.342
Latvia	3.472	1.203	1.104	5.828	3.471	1.52	0.376	6.348
Lithuania	7.872	1.034	5.839	9.902	7.871	1.318	5.261	10.429
Luxembourg	10.484	1.002	8.47	12.403	10.484	1.268	7.912	12.899
Malta	5.787	1.379	3.024	8.44	5.788	1.78	2.211	9.208
Norway	7.575	1.209	5.179	9.924	7.577	1.531	4.474	10.489
Poland	8.146	1.094	5.944	10.246	8.146	1.4	5.427	10.922
Portugal	9.607	1.305	7.086	12.207	9.607	1.67	6.249	12.805
Romania	12.175	2.286	7.601	16.582	12.173	2.921	6.259	17.741
Slovakia	6.541	1.185	4.184	8.839	6.541	1.512	3.506	9.453
Slovenia	6.518	1.092	4.339	8.624	6.518	1.401	3.694	9.206
Spain	6.361	1.218	4.006	8.792	6.361	1.568	3.179	9.343
Sweden	8.278	1.448	5.392	11.086	8.278	1.839	4.645	11.865
Switzerland	6.689	1.012	4.688	8.66	6.69	1.307	4.161	9.285
Netherlands	7.281	1.008	5.235	9.197	7.28	1.29	4.736	9.801
Turkey	10.444	1.213	8.051	12.809	10.445	1.554	7.404	13.505
United_Kingdom	10.332	1.69	6.995	13.64	10.332	2.154	6.081	14.535