Willingness to pay or willingness to accept? An experimental study on secondhand smoke

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Abstract

The anomaly between willingness to pay (WTP) and willingness to accept (WTA) invokes a well-established discussion in the stated preference literature. The debate involves which of the two is a better welfare measure. Although a few studies have tried to provide some insights, many researchers settle for eliciting WTP rather than WTA. However, WTA is a better welfare measure in some circumstances, especially in situations involving spillover effects and property rights. We investigate one of such situations and provide insights into how individuals in heterogeneous healthcare systems (private (U.S.) and public (U.K.)) value the effects of a spillover. First, we use choice experiments and contingent valuation techniques to quantify the attributes of secondhand smoke (SHS) health risks, focusing on generating cross-country comparisons. We then compare the WTP and WTA welfare estimates. We find that agents differ significantly in valuing "external" health risks. Hence, this study uncovers an aspect of health risks valuation lacking in the literature. We also find that the two welfare measures differ significantly; thus, we contribute to the ongoing debate between WTP and WTA.

Keywords: Secondhand Smoke; Health Risks; WTP; WTA; Choice Experiment, Contingent Valuation.

JEL Codes: Q51; Q53; I12.

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1 Introduction

A growing body of literature is dedicated to the debate on whether to elicit willingness to pay (WTP) or willingness to accept (WTA) as a welfare measure. A handful of studies suggest that it depends on two factors: (1) the nature of the good or service under consideration and (2) property rights (Carson *et al.*, 2001; Hammitt, 2002; Knetsch, 2007; Kim *et al.*, 2015; Whittington *et al.*, 2017).

Thus, when an individual has the right to an improvement and yet does not obtain it, WTA is appropriate. On the other hand, the individual is expected to pay for the improvement if they are not entitled, in which case, WTP is elicited. In other words, the individual pays to avoid degradation or pollution. The property right argument implies that an agent with the right to produce negative externalities should be paid if governments want to curtail such activities. However, Knetsch (2006) argues that community norms and feelings should be considered too.

Because of the anomaly between WTP and WTA, where the latter in most cases outweighs the former for the same good due to loss aversion (Kim *et al.*, 2015; Whittington *et al.*, 2017), the National Oceanic and Atmospheric Administration (NOAA) panel recommends eliciting WTP instead of WTA (Arrow *et al.*, 1993).[1]

However, it is argued that researchers should not shy away from eliciting WTA when it is the most suitable (Knetsch, 1990; Haab and McConnell, 2002; Johnston *et al.*, 2017; Whittington *et al.*, 2017). A well-designed discrete choice (or even more preferably, choice experiments (CE)) WTA question format is incentive-compatible and circumvents the weaknesses of open-ended questions (Whittington *et al.*, 2017). Applying WTP when WTA should instead be used can have massive policy implications (Knetsch, 1990; Carson *et al.*, 2001).

A theoretical study by Randall and Stoll (1980) shows that WTP and WTA values should be close, except for income effects. Hanemann (1991) extends this by explicitly showing that the income and substitution effects cause the divergence between the two. The author argues that WTP and WTA would differ significantly with goods with few or no substitutes like life. However, if there are substitutes, the two will converge. Again, while WTP depends on income (which is finite), WTA is infinite. Thus, Hanemann (1991) concludes that the dichotomy between the two is not an indication of a wrong methodology or data collection. Rather it depends on how respondents perceive the survey. Shogren *et al.* (1994) test this empirically applying the auction technique to a market good with close substitutes and a nonmarket good with imperfect substitutes such as reduced health risk due to Clostridium perfringens, Trichinella, Campylobacter, Salmonella, and Staphylococcus aureus. The results of the market good showed no significant difference between WTP and WTA. In contrast, in the second case involving nonmarket goods, WTA significantly outstrips WTP.

However, Viscusi and Huber (2012) argue that the gap is primarily due to the reference point effects associated with cost. In contrast, the income effects cannot account for the discrepancy. Likewise, using the CV method, Nduka (2020) elicits WTP to avoid contracting COVID-19 disease and WTA compensation for a lockdown. The respondents were willing to pay twice

[1] It is worthy to note that the tendency to overstate WTA is primarily seen in contingent valuation (CV) with open-ended questions.

more than they were willing to accept. Thus, Hanemann's theory fails to hold in such an instance.

Aside from the early studies cited above, a growing number of studies focus on eliciting WTP to prevent or reduce air pollution, chronic diseases, and mortality, using a CV direct approach (Hammitt and Haninger, 2010; Andersson *et al.*, 2015; Tubeuf *et al.*, 2015; Hollinghurst *et al.*, 2016). In addition, a handful applies the indirect CE method to quantify the attributes (Johnson *et al.*, 2000; Gerard *et al.*, 2003; Hole, 2008; Adamowicz *et al.*, 2011; Huang *et al.*, 2018). A fundamental feature here is that these studies all estimated WTP and not WTA due to perhaps the two factors mentioned above.

We contribute to the existing literature on the WTP-WTA anomaly by investigating non-smokers' willingness to pay to avoid secondhand smoke (SHS) exposure and their willingness to accept compensation for exposure. Unlike previous studies, the issue of SHS exposure is different because individuals are entitled to clean air free from tobacco smoke (WHO, 2005; UNEP, 2019a,b). At the same time, smokers have the right to smoke in non-smoke-free zones whether or not a nonsmoker is present. Aside from this, we hypothesize that agents would differ in their valuation of SHS health risks, depending on the type of healthcare system practiced in their countries (private or publicly-funded systems). Furthermore, evidence suggests that agents' valuation for the same good or service differs, depending on whether the provisioning mechanism is private or public (Guo *et al.*, 2006).

We employ stated preference methods widely used to value health risks due to a lack of market data. The methods involve creating a hypothetical market in which respondents make choices that involve trade-offs between health risks and wealth, or payoff (see Andersson *et al.*, 2019). While we use the CV technique to elicit WTP, CE was used to elicit WTA. Hence, avoiding the incentive for respondents to overstate their WTA. This study is the first to quantify SHS health risks. In addition, it is the first to provide insight into how agents in different healthcare systems value negative externalities like SHS. This would enhance policymakers' understanding of individuals' behavior towards potential health risks.

This paper's remainder is divided as follows: In section 2, we give the methodology, including the experimental design and data collection. We then proceed with the results in section 3 and a robust discussion of our findings in section 4. We conclude in section 5.

2 Methodology

2.1 Overview

We estimate both respondents' WTA health harm compensation due to SHS and WTP to prevent exposure. Here, WTA is the amount of money that will keep an individual on a higher indifference curve (or the amount of money required to compensate the individual for health harms or losses) but on the same health risk level (R_0). Conversely, WTP is the amount that will be taken from the individual for a change from the status quo risk level (R_0) to an improved health level (R_1), while he is as well off as before.

We show the framework as follows: Assume an agent n with wealth w_0 and status quo health risk R_0. The utility functions of n are given as

$$u(R_0^n, w_0^n) = u(R_1^n, w_0^n - WTP^n) \tag{1}$$

$$u(R_0^n, w_0^n + WTA^n) = u(R_0^n, w_1^n) \tag{2}$$

where WTP (compensating variation) is the amount of money n is willing to pay to prevent exposure to SHS, WTA (equivalent variation) is the amount n is willing to accept as compensation for health losses or harms due to SHS, and R_1 is an improved health profile.

2.2 The Experimental Design

Table 1 contains the attributes and their levels. The choice of attributes and levels were informed by extensive literature review and pilot studies. The attributes relate to sufficient evidence of health effects of SHS to adults, such as stroke, lung cancer, and coronary heart disease (see CDC, 2020; The Tobacco Atlas, 2021). Other attributes used are emotional distress and monetary payoffs (reduction in health insurance premium or tax as the case may be).

These attributes and their levels in the full factorial design yield 512 (2×4^4) different alternatives. These would be $512 \times 511/2 = 130,816$ pairs of choice sets, which will be too much for each respondent to complete. Thus, we constructed sixteen choice sets blocked into two pairs of eight choices using the D-efficient design. Without priors, and following the best practice guidelines, we set the attributes coefficients at zero (see Hole, 2008, 2017; Lancsar *et al.*, 2017).

First, we designed the efficient experiment in Stata. Second, we transformed it into an Excel spreadsheet. Third, we wrote a Stata command in advanced format TXT files and constructed the CE tables using a hypertext markup language (HTML). Fourth, we randomized the order in which the choice sets were presented to participants within and across blocks using the advanced randomization option in Qualtrics. Finally, we wrote another Stata code that automatically transformed the collected data and made it ready for use (see Weber, 2019).

The choice experiment scenario presented in Table 2 asked participants to imagine that they had to choose between two bundles of potential health risk levels due to SHS exposure, including a monetary payoff. Before the information presented in Table 2 and Table 3, respondents were given a general introduction about the sources, effects, and meaning of each disease associated with SHS. Also, a brief country-specific statistics on the risk levels of the respective diseases were provided. This was to ensure that respondents focus on the subject. We provided a question that asked respondents to rank the attributes to their order of dislike before proceeding with the choice tasks. Figure 1 and Figure 2 illustrate the choice sets administered to U.S. and U.K. respondents, respectively.

Table 1: SHS Risk Attributes and Levels

Attribute	Levels
Stroke risk	10%, 15%, 20%, 25%
Lung cancer risk	8%, 18%, 28%, 38%
Coronary heart disease risk	5%, 15%, 25%, 35%
Emotional distress risk	low, high
Reduction in health insurance premiums (tax)*	0%, 10%, 20%, 30%

*We used health insurance premiums for U.S. participants and tax for U.K. respondents.

Table 2: Abridged Choice Experiment Scenario

Introduction	Secondhand smoke (SHS) effects are well known, such as stroke, lung cancer, coronary heart disease, and others. As a result, governments have implemented different smoke-free laws. However, people are still exposed to SHS. Besides, it is unclear how nonsmokers view exposure to SHS. Furthermore, the effects have not been quantified. Thus, we want to use this study to quantify the effects of SHS.
Task	Although it is hard to measure the risks attached to your SHS exposure level, imagine that you can choose which level of risks you are exposed to in your current situation. You will see eight choice scenarios as you proceed. Each scenario labeled as options 1 and 2 contains potential risk levels and a reduction in your current monthly health insurance premium (tax) as compensation. We would like you to choose which option you would prefer assuming that they are real choices.

Among the following Secondhand Smoke Risk options, which one do you prefer?

	Option 1	Option 2
Stroke risk	10%	15%
Lung Cancer risk	8%	28%
Coronary Heart Disease risk	15%	35%
Reduction in your Health Insurance Premiums	-20%	-30%
Emotional Distress risk	High	Low

	Option 1	Option 2
Your choice:	○	○

Figure 1: Example of Choice Task (U.S.)

Among the following Secondhand Smoke Risk options, which one do you prefer?

	Option 1	Option 2
Stroke risk	20%	15%
Lung Cancer risk	28%	18%
Coronary Heart Disease risk	15%	35%
Reduction in your Tax	-30%	-0%
Emotional Distress risk	Low	High

	Option 1	Option 2
Your choice:	○	○

Figure 2: Example of Choice Task (U.K.)

2.3 Contingent Valuation

The CV scenario is presented in Table 3. We asked respondents to imagine a policy that would change their current level of SHS exposure. The payment vehicle was a one-off increment in their one-year income tax. The question asked them to state the minimum and maximum WTP to prevent SHS exposure. It is a common practice to elicit maximum WTP only, but we included the minimum to ensure that zero responses in both cases signify a protest. We provided a cheap talk that reminded respondents to take the scenario as real and to be honest.

Table 3: Abridged Contingent Valuation Structure

Scenario	Imagine there is a proposed program that would affect your current status. Here, we are trying to assess how much money people like you would be willing to pay for a change from the current situation to a situation where they are not exposed to SHS. The amount would be an increment in your income tax for one year only.
Question	What is the (minimum) maximum you would be willing to pay this year in addition to your current income tax?
Cheap talk	It has been reported that many respondents answering these types of questions indicate more amount than they are willing to pay in reality. Please take these questions as if they are actual decisions. Do not agree to pay any amount you cannot afford.

(see Contu and Mourato, 2020, for a similar cheap talk).

2.4 Survey and Data Collection

Besides the first part that provided a brief introduction of the study to respondents and the second that contained the University of Exeter's generic consent questions, the survey had five blocks. In part one, we asked questions relating to respondents' knowledge and view about SHS. Part two contained a few questions about their health status. Part three had WTP elicitation questions, including a question that asked respondents who indicated a zero WTP to state their reasons. Those who indicated a positive value were also asked to show how sure they were to pay the amount in reality on a ten-point Likert scale, ranging from not sure to very sure. In block four, we presented the sixteen choice sets in two blocks of eight each. Respondents were randomly assigned these evenly. We asked a few socio-demographic questions in part five, including two debriefing questions that elicited respondents' general views about SHS and the survey. The study terminated with a further explanation about SHS and how respondents can access the study's findings in the future.

Participants were recruited and paid on the Prolific platform - a reputable research agency based in Oxford, United Kingdom. We recruited participants 18 years and over who were living in the U.S. and U.K. In both countries, we used participants who were nonsmokers. Additionally, U.S. respondents were those that had health insurance. The data collection lasted from September 14, 2020, to January 9, 2021. We conducted two pilot studies on both U.S. and U.K populations. Following these, we adjusted the survey and included or removed specific questions. We surveyed about 600 participants in each of those countries. After data cleaning, 541 and 554 choice experiment responses from the U.S. and U.K. were used in the estimation, giving 8,656 and 8,864 observations, respectively. However, after deleting zero responses from the CV data, 364 and 363 observations were used, respectively.

2.5 Econometric Technique

CE Models

It is plausibly assumed that each decision-maker interprets utility in terms of attributes through a common functional form (Hensher *et al.*, 2005). Suppose an individual n faces a set of alternative health scenarios denoted as J and $j = 1, ..., J$. Let U_{njt} represents the utility the nth individual derives from choosing the jth alternative in choice set t.

The individual's utility is decomposed into representative (deterministic) and random parts. While the econometrician observes the representative part via estimation of model parameters, she is not aware of the random part (Train, 2009). The model can be specified in the additive form as:

$$U_{njt} = \beta_1 stroke_{njt} + \beta_2 cancer_{njt} + \beta_3 hrtdisease_{njt} + \beta_4 emodistress_{njt} + \beta_5 payoff_{njt} + \epsilon_{njt} \quad (3)$$

where β_1 to β_5 are the parameters to be estimated; $stroke_{njt}$ is stroke risk, $cancer_{njt}$ is lung cancer risk, $hrtdisease_{njt}$ is coronary heart disease risk, $emodistress_{njt}$ is the risk of having emotional distress, $payoff_{njt}$ is the reduction in health insurance premium or tax as the case may be, and ϵ_{njt} is the random error term.

Suppose we assume that the random terms are independently and identically distributed (IID) type I extreme value. In that case, this yields the conditional logit model of McFadden (1974).

$$P_{njt} = \frac{exp(\beta_1 stroke_{njt} + ... + \beta_5 payoff_{njt})}{\sum_{j=1}^{J} exp(\beta_1 stroke_{njt} + ... + \beta_5 payoff_{njt})} \quad (4)$$

This model makes strong assumptions that the errors are IID, which leads to the second assumption of independence of irrelevant alternatives (IIA). This assumption states that the ratio of the probabilities of choosing any option over another ($\frac{P_j}{P_i}$) is not affected by the presence or absence of any other alternatives in the choice set. Thus, it treats respondents' preferences and taste as homogeneous. However, in reality, the deterministic and random attributes of utility may depend on each other, and this correlation leads to the bias of the utility parameters.

As a result, more advanced models such as mixed logit (MXL) or random parameters logit (RPL), and generalized multinomial logit (G-MNL) are applied. The mixed logit model is highly flexible and guarantees a wide range of choices to specify individual-specific unobserved heterogeneity, although being fully parametric (Hensher and Greene, 2003). It overcomes the IIA assumption by treating the coefficients that enter the model as varying across individuals but being constant across choice occasions for each decision-maker (Train, 2009). In the mixed logit model, the unobserved part, ϵ_{nit} is independently and identically distributed extreme value over people and alternatives. The β_n is a vector of coefficients [vector of parameter weights] representing individual-specific tastes with density $f(\beta/\theta)$, where θ represents, say, mean and covariance of the β's in the population (Train, 2009). These conditional parameter estimates are strictly same-choice-specific parameters or the subpopulation's mean that makes similar choices when faced with the same choice scenarios. It is an important distinction since it is impossible to establish every individual's distinct set of estimates. Rather a mean estimate for the subpopulation who made the same set of choices is identified (Hensher *et al.*, 2005; Czajkowski *et al.*, 2017). It is worth noting that the MXL model collapses to the CL model if there is no unobserved heterogeneity. In which case, the CL can be reliable.

The probability that the decision-maker (n) makes a sequence of choices conditional on observing β is the product of the logit formula as:

$$S_n = \int \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\beta_1 stroke_{njt} + ... + \beta_5 payoff_{njt})}{\sum_j exp(\beta_1 stroke_{njt} + ... + \beta_5 payoff_{njt})}]^{y_{njt}} f(\beta/\theta) d\beta \tag{5}$$

where y_{njt} is equal to 1 if j alternative is chosen and to 0 otherwise, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$. The econometrician determines β's distribution through intuition and statistical tests. While parameters in eq. (4) can be estimated using the maximum likelihood (ML) method, the integral in eq. (5) can only be simulated. Despite the MXL model's appealing qualities and its wide application, it is not free from criticisms. The model still assumes that the random error is IID.

The G-MNL models heterogeneity in taste as scale heterogeneity. This means that the scale of the error term is more significant for some respondents than others. In other words, the idiosyncratic error terms are more critical to some decision-makers than the observed attributes. Thus, it accounts for some respondents' random behavior by treating the attributes coefficients as a continuous mixture of scaled normals (Fiebig *et al.*, 2010; Lancsar *et al.*, 2017). However, the MXL model with correlated coefficients may provide a better fit. It is best practice to estimate all the models and choose the best using AIC and BIC criteria.

For convenience, we will specify the G-MNL as (Lancsar *et al.*, 2017):

$$U_{njt} = X'_{njt}\beta_n + \epsilon_{njt} \tag{6}$$

where X'_{njt} is a vector of respondent n observed attributes, and β_n is a vector of respondent-specific coefficients.

$$\beta_n = \lambda_n \beta + \gamma \eta_n + (1-\gamma)\lambda_n \eta_n \tag{7}$$

No scale heterogeneity assume $\lambda_n = \lambda$, and G-MNL collapses to MXL. Further, there is no preference heterogeneity if $\eta_n = 0$, thus, $\beta_n = \lambda_n \beta$. Two variants of G-MNL emerge if γ is restricted to either zero (scaled random coefficients) or one (scaled means of the coefficients). In both cases, we will have $\beta_n = \lambda_n(\beta + \eta_n)$ and $\beta_n = \lambda_n \beta + \eta_n$.

Another model that captures heterogeneity differently is the latent class logit model (LCM), because in modeling taste heterogeneity, corner solution may arise when a significant subpopulation of the population places a zero weight on some attributes and not accounting for this may not reveal the true nature of heterogeneity (Hensher, 2014). In modeling spatial heterogeneity, individuals are assumed to be sorted into a set of different classes or clusters (c), with the researcher not having prior knowledge of the cluster each belongs. Thus, preferences are homogeneous within classes but differ across classes (Greene and Hensher, 2003).

The difference between MXL and LCM is that in the former, parameters are individual-specific, while in the latter, it is class-specific. The utility is assigned a number based on the class to which a respondent belongs (Czajkowski *et al.*, 2017). Further, while the MXL model assumes a full parametric distribution of the parameters, the LCM is semiparametric. This gives the analyst liberty not to make any distributional assumptions about individual heterogeneity (Greene and Hensher, 2003). While in the MXL, the coefficients are continuously distributed, they follow a discrete distribution in the LCM. Furthermore, although the two models can account for correlations between the coefficients, the analyst needs to specify this option in MXL while the LCM implicitly allows the coefficients to correlate. Thus, the choice of the distribution of β in the LCM is not controversial. Finally, the MXL model is estimated through maximum simulated likelihood (SML), while the LCM is estimated via the ML approach (Hole, 2008).

The LCM probability that n makes a sequence of choices is specified as:

$$S_n = \sum_{c=1}^{C} H_{nc} \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(\beta_{1c} stroke_{njt} + ... + \beta_{5c} payoff_{njt})}{\sum_{j=1}^{J} exp(\beta_{1c} stroke_{njt} + ... + \beta_{5c} payoff_{njt})}]^{y_{njt}} \tag{8}$$

where H_{nc} is the probability that n belongs to class c, which gives the multinomial logit:

$$H_{nc} = \frac{exp(\gamma_c' Z_n)}{\sum_{=1}^{C} exp(\gamma_c' Z_n)} \tag{9}$$

where Z_n is a vector of observed characteristics of respondent n and γ_c parameter is normalized to zero for model identification (Greene and Hensher, 2003; Andersson *et al.*, 2019; Yoo, 2020).

The marginal WTA compensation for SHS exposure is derived by partially differentiating eq. (3) with respect to each of the attributes and dividing each by the monetary attribute. As per the LCM, this is simulated using the class-specific marginal utilities.

$$mWTA = \frac{\partial U_{njt} / \partial stroke_{njt}}{\partial U_{njt} / \partial payoff_{njt}} = \left| \frac{\beta_1}{\beta_5} \right| \tag{10}$$

CV Models

One variant of CV uses open-ended questions that ask respondents to state their maximum WTP for an improvement in health conditions (see Donaldson *et al.*, 1998; Jonas *et al.*, 2010; Contu and Mourato, 2020). It is common to use ordinary least squares (OLS) regression to analyze the data in such a situation. However, this becomes problematic if the data set contains a substantial amount of zeros (Donaldson *et al.*, 1998) because of protest against paying for others' health-risk behavior. It may be advisable to exclude the protest responses (Adamowicz et al., 2011; Johnston et al., 2017). The OLS regression is given by

$$WTP_n = \alpha + X_n'\beta + \epsilon_n \tag{11}$$

where WTP_n is the willingness to pay for respondent n, X_n is a vector of the explanatory variables, β is the vector of coefficients, ϵ_n is the error term. Equation (11) is estimated by minimizing $\sum_n \epsilon_n^2$.

This model's limitation is that it only gives the average relationship between the conditional mean of the dependent variable and a set of regressors, giving only a partial insight into the relationship (Cameron and Trivedi, 2010). Furthermore, even when the protest responses are removed from the estimation, there may still be some outliers, and because of the asymmetric distribution of the WTP, it is best practice to use the natural logarithm of WTP. Moreover, when such is done, if the smallest value of WTP is 1, it becomes 0.

The ensuing argument invokes the use of a censoring model such as the Tobit model. It assumes that the error term follows a censored normal distribution. The model is specified as:

$$E[WTP_n/X_n] = \Phi(\beta' X_n/\sigma)(\beta' X_n + \frac{\sigma\phi(\beta' X_n/\sigma)}{\Phi(\beta' X_n/\sigma)}) = \Phi(\beta' X_n/\sigma)(\beta' X_n) + \sigma\phi(\beta' X_n/\sigma) \tag{12}$$

where Φ and ϕ are the cumulative density function and standard normal density function, respectively, and σ is the standard deviation of ϵ_n. Here, the conditional mean function depends on the relationship between the dependent variable and a set of regressors and also on the probability that the dependent variable has a value that is greater than zero (Donaldson et al., 1998).

Another model favored over the OLS is quantile or median regression. It gives a complete view of the relationship between the dependent and independent variables at different quantiles in WTP distribution. Unlike the OLS regression, this model provides more robust results because it handles outliers efficiently. It is a semiparametric method, which does not make assumptions about the distribution of the error term (Cameron and Trivedi, 2005, 2010). It is given by

$$WTP_n = \alpha + X_n'\beta^q + \epsilon_n^q \tag{13}$$

where $q \in (0, 1)$ represents the quantile specified, the coefficients β^q are realized by minimizing the weighted sum of the absolute values of ϵ_n^q.

3 Results

3.1 Descriptive Statistics

Table 9 presents the key variables used in the analyses. We present the sample statistics of the pooled data, U.S., and U.K. data. For simplicity, we will focus on comparing U.S. and U.K. figures. In most cases, the samples are identical. The majority of the U.S. sample are males (55%) compared to 36%. More respondents are exposed to SHS at home and in private vehicles in the U.K. (35%) than in the U.S. (16%). Nearly half of respondents (48%) are living with a partner/spouse in the U.S. compared to 53% in the U.K. Only 4% of U.S. respondents' partner/spouse smoke relative to 6% in the U.K. While 38% of U.S. respondents have/had serious ill-health, it is 40% in the U.K. The majority of respondents in the U.S. (82%) and U.K. (78%) indicated that SHS causes them distress. Respondents were asked to show on a ten-scale Likert of poor to excellent their knowledge about SHS effects. Most of the respondents (58%) in the U.S. and 53% of U.K. respondents reported having good knowledge, only 19% compared to 13% of respondents indicated that they have excellent knowledge. The income distributions of both samples are pretty the same. The vast majority of respondents (64%) in the U.S. relative to 69% of U.K. respondents fall within the $1,100-$5,600 band.

Other variables not used in the estimations but provide more insight into our samples' characteristics are presented in Table A3. The average age of U.S. respondents is 31.4 compared to 32.1 years. Only 24% (23%) of respondents have university degree; and 73% (69%) are in full employment; 63% (81%) are whites. It is worth noting that most U.K. respondents (72%) are exposed to SHS between four to seven times a week compared to 45% of U.S. participants. As per health-risk behaviors, more U.K. respondents (80%) consume alcohol compared to 56% of U.S. respondents. Further, they consume 3.4 glasses per week on average compared to 2.1 glasses reported by U.S. respondents.

Table 4: Sample Statistics

Variable	Description	Mean (Std. Dev.)		
		Pooled	U.S.	U.K.
Male	=1 if male	0.46 (0.499)	0.55 (0.498)	0.36 (0.482)
Exposure place	=1 if exposed at home & vehicle	0.26 (0.437)	0.16 (0.369)	0.35 (0.478)
Living with partner/spouse	=1 if living with partner	0.50 (0.500)	0.48 (0.500)	0.53 (0.499)
Smoking partner	=1 if partner/spouse smokes	0.05 (0.219)	0.04 (0.193)	0.06 (0.243)
Health status	=1 if suffered/suffering from serious ill-health	0.39 (0.488)	0.38 (0.485)	0.40 (0.490)
SHS distresses	=1 if distressed by secondhand smoke	0.80 (0.400)	0.82 (0.384)	0.78 (0.417)
KSHS: Good	=1 if respondent has good knowledge about SHS risks	0.56 (0.497)	0.58 (0.494)	0.53 (0.499)
KSHS: Excellent	=1 if respondent has Excellent knowledge	0.16 (0.368)	0.19 (0.395)	0.13 (0.336)
*Income: $1,100-$5,600	=1 if yes	0.66 (0.473)	0.64 (0.481)	0.69 (0.463)
Income: $5,601-$10,100	=1 if yes	0.08 (0.273)	0.15 (0.359)	0.01 (0.105)
Income: More than $10,100	=1 if yes	0.04 (0.205)	0.07 (0.258)	0.02 (0.128)

Note: *Monthly disposable income.

3.2 Self-Reported Views on Smoking

For exploratory reasons, we elicited respondents' attitudes towards smoking. First, they were asked: "Should governments ban smoking at home and in private vehicles when a nonsmoker is present?" An equal proportion of U.S. respondents (37%) voted yes and no, respectively. At the same time, 26% are indifferent. In the U.K., 60% of respondents answered in affirmative, only 16% voted no, and 24% are indifferent. Second, we asked respondents: "Should governments empower kids exposed to SHS at home to sue the smoker when they become adults?" Again, there are cross-country discrepancies. Only 23% of U.S. respondents answered yes, 32% indicated no, and 45% are indifferent. In comparison, 33% of U.K. respondents favor the law, 27% are against it, and the majority 40% are indifferent. These discrepancies could be because more U.K. respondents are exposed to SHS in those places than U.S. participants.

3.3 Results from Choice Experiments

To ensure that respondents did not engage in unethical practices, we checked the possibility of consistently choosing a particular option before the estimation (see Viscusi *et al.*, 1991). We did not find any abnormal responses, but incomplete responses were deleted. Following best practice guidelines (see Johnston *et al.*, 2017; Lancsar *et al.*, 2017), we started with a simple model such as the conditional logit (or fixed effect model) in eq. (4) and estimated more advanced ones like the mixed logit/random parameters logit specified in eq. (5), and generalized multinomial logit (G-MNL) in eq. (7). While the conditional logit model treats individual preferences as homogeneous, the more advanced models account for heterogeneity in taste and scale. We model all the variables as continuous, except the emotional distress variable coded as a dummy. See Table A1 and Table A2 for the summary statistics of the choice models variables.

In MXL I, we treat all parameters as normally distributed, except the payoff parameter, whereas all parameters are normally distributed in MXL II. MXL III accounts for correlation among the random coefficients. Since each respondent completed eight tasks, we anticipate correlated responses. Failure to account for this could bias the results (see Carlsson *et al.*, 2010).

In the G-MNL specification, we restrict gamma to zero to account for scale heterogeneity (differences in error variance). Failure to account for this could produce biased estimators (Haab *et al.*, 1999; Fiebig *et al.*, 2010; Johnston *et al.*, 2017). This model collapses to MXL if the coefficient of the scale parameter turns out to be statistically insignificant. The MXL and G-MNL models were estimated through maximum simulated likelihood with 500 Halton draws. We circumvent confounding effects on our results by not including covariates.

Concerning the coefficients' interpretation of the results in Table 5 and Table 6, it should be noted that signs of the attributes' coefficients relate to how each affects the dependent variable (choice probability). A negative coefficient shows the probability of a decrease in utility. Overall, the signs of the coefficients are consistent with a priori expectation. All the coefficients are statistically significant. U.S respondents prefer policies with a higher reduction in health insurance premiums and lower SHS health risks. However, the coefficient of a tax reduction in

Table 6 is not statistically different from zero. It is worthy to note that respondents prefer a higher probability of reducing the risk of emotional distress than other risks.

It can be seen that the standard deviation coefficients are significant, meaning that there is evidence of heterogeneity in taste across our samples. Further, the scale parameter in the G-MNL is significant, indicating scale heterogeneity. In Table 5, the AIC and BIC favor MXL II, where all the coefficients are treated as random. However, the outcome is mixed in Table 6, where the AIC favors MXL III, while BIC prefers MXL II. The log-likelihood function is higher in MXL III. Revelt and Train (1998) recommended modeling the monetary variable as fixed; however, like our results, Meijer and Rouwendal (2006) and Hole (2008) found that allowing it to vary fits their data better.

Table 5: Estimates of Choice Models (U.S.)

	CL	MXL I	MXL II	MXL III	G-MNL
Variable	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)
Stroke risk	-0.051*** (0.004)	-0.078*** (0.008)	-0.093*** (0.009)	-0.082*** (0.010)	-0.114*** (0.019)
Lung cancer risk	-0.065*** (0.003)	-0.111*** (0.007)	-0.126*** (0.009)	-0.118*** (0.007)	-0.194*** (0.042)
Coronary heart disease risk	-0.042*** (0.002)	-0.072*** (0.005)	-0.081*** (0.006)	-0.084*** (0.007)	-0.122*** (0.024)
Emotional distress risk	-0.583*** (0.049)	-0.810*** (0.081)	-0.885*** (0.094)	-0.754*** (0.099)	-1.414*** (0.321)
Health insurance premium	0.008*** (0.002)	0.015*** (0.003)	0.018*** (0.004)	0.013*** (0.004)	0.017*** (0.006)
Standard Deviation					
Stroke risk		0.060*** (0.018)	0.051* (0.027)	0.084*** (0.018)	0.047 (0.050)
Lung cancer risk		0.084*** (0.006)	0.098*** (0.007)	0.086*** (0.006)	0.133*** (0.028)
Coronary heart disease risk		0.061*** (0.006)	0.071*** (0.006)	0.072*** (0.008)	0.090*** (0.017)
Emotional distress risk		0.928*** (0.104)	0.982*** (0.118)	0.948*** (0.113)	1.218*** (0.287)
Health insurance premium				0.054*** (0.007)	
τ					-1.051*** (0.193)
Observations	8656	8656	8656	8656	8656
Number of respondents	541	541	541	541	541
LL	-2052.3809	-1892.622	-1870.189	-1867.287	-1887.0305
AIC	4114.762	3803.244	3760.378	3764.574	3794.061
BIC	4150.092	3866.838	3831.038	3870.564	3864.721

***p <0.01, **p <0.05, *p <0.10. Standard errors (in parentheses) are robust. Note: *CL* conditional logit, *MXL* mixed logit, *G-MNL* generalized multinomial logit. MXL and G-MNL models were estimated with Stata 16.

Table 6: Estimates of Choice Models (U.K.)

	CL	MXL I	MXL II	MXL III	G-MNL
Variable	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)
Stroke risk	-0.049*** (0.004)	-0.072*** (0.006)	-0.083*** (0.007)	-0.093*** (0.008)	-0.169*** (0.039)
Lung cancer risk	-0.071*** (0.003)	-0.121*** (0.007)	-0.134*** (0.009)	-0.128*** (0.008)	-0.258*** (0.064)
Coronary heart disease risk	-0.044*** (0.002)	-0.075*** (0.005)	-0.083*** (0.005)	-0.083*** (0.007)	-0.154*** (0.042)
Emotional distress risk	-0.670*** (0.050)	-0.905*** (0.079)	-0.984*** (0.089)	-0.9034*** (0.099)	-1.978*** (0.452)
Tax	0.0004 (0.002)	0.003 (0.004)	0.005 (0.004)	0.001 (0.004)	-0.004 (0.011)
Standard Deviation					
Stroke risk		-0.037*** (0.007)	0.010 (0.014)	0.079*** (0.012)	-0.037 (0.0312)
Lung cancer risk		0.095*** (0.007)	0.109*** (0.008)	0.099*** (0.007)	0.176*** (0.032)
Coronary heart disease risk		0.051*** (0.005)	0.063*** (0.008)	0.059*** (0.008)	0.039*** (0.014)
Emotional distress risk		0.817*** (0.099)	0.749*** (0.126)	0.846*** (0.094)	1.546*** (0.602)
Tax				0.056*** (0.006)	
τ					-1.240*** (0.209)
Observations	8864	8864	8864	8864	8864
Number of respondents	554	554	554	554	554
LL	-2049.3869	-1853.223	-1829.104	-1816.832	-1835.985
AIC	4108.774	3724.446	3678.209	3663.664	3691.969
BIC	4144.223	3788.253	3749.106	3770.01	3762.867

***p <0.01, **p <0.05, *p <0.10. Standard errors (in parentheses) are robust. Note: *CL* conditional logit, *MXL* mixed logit, *G-MNL* generalized multinomial logit. MXL and G-MNL models were estimated with Stata 16.

3.4 Results from Latent Class Model

Since the MXL model results show heterogeneity in our samples, we use a latent class logit model to sort respondents into different groups comprising identical preferences. We estimate three classes, which are determined using AIC and BIC. It is assumed that preferences are homogeneous within a class but heterogeneous across classes (Greene and Hensher, 2003). Ultimately, the model allows us to see how respondents in each class value the attributes. In our latent class model, class membership is explained by a constant. Thus, the likelihood of belonging to each group is constant across respondents (see also Adamowicz *et al.*, 2011; Hole, 2008).

We model the payoff as homogeneous in Table 7, while we allow it to vary in Table 8. Specifying it this way gives our data a better fit. All the coefficients in Table 7, have the expected signs and are statistically significant, except the coefficient of emotional distress in class 3. This shows that emotional risk is not paramount to about 30% of respondents. Indeed, SHS may not cause emotional distress to a nonsmoker, depending on where their exposure takes place and the frequency. Furthermore, the log-likelihood is similar to the mixed logit model in Table 7, where all the coefficients are allowed to vary. This is consistent with the findings of Hole (2008). The majority of respondents belong to class 1, followed by classes 3 and 2, respectively.

As per the U.K. results, Table 8 shows that all the coefficients have the expected signs, except in class 2, where the tax coefficient is negative. It can be seen that the results vary substantially across classes. Most of the coefficients in class 2 are statistically significant, while only coronary heart disease risk and emotional distress are significant in class 1. In class 3, stroke and lung cancer risks are significant. The vast majority of respondents belong to class 1, followed by classes 2 and 3, respectively. Although the results of CL, MXL, and G-MNL presented in Table 6 show that the tax coefficient is not significant, the latent class model helps us see that it is significant for class 3 respondents.

Table 7: Latent Class Logit Model Estimates (U.S.)

	Class 1	Class 2	Class 3
Variable	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)
Stroke risk	-0.117*** (0.014)	-0.035*** (0.009)	-0.047*** (0.018)
Lung cancer risk	-0.088*** (0.010)	-0.012*** (0.005)	-0.339** (0.174)
Coronary heart disease risk	-0.093*** (0.009)	-0.005* (0.005)	-0.051*** (0.0188)
Emotional distress risk	-1.106*** (0.172)	-0.240*** (0.083)	-2.020 (1.704)
Health insurance premium	0.011*** (0.003)		
Constant	0.362* (0.210)	-0.097 (0.189)	
Class share	0.429	0.272	0.299
Observations	8656		
Number of respondents	541		
LL	-1870.319		

***p <0.01, **p <0.05, *p <0.10. Standard errors are in parentheses.
Note: Health insurance premium is specified as homogeneous.

Table 8: Latent Class Logit Model Estimates (U.K.)

	Class 1	Class 2	Class 3
Variable	Coeff. (S.E.)	Coeff. (S.E.)	Coeff. (S.E.)
Stroke risk	-0.013 (0.010)	-0.135*** (0.018)	-0.079*** (0.022)
Lung cancer risk	-0.001 (0.006)	-0.126*** (0.017)	-0.296*** (0.040)
Coronary heart disease risk	-0.019*** (0.004)	-0.098*** (0.012)	-0.032 (0.026)
Emotional distress risk	-0.377*** (0.110)	-1.757*** (0.381)	-0.778 (0.479)
Tax	0.009 (0.008)	-0.037*** (0.015)	0.048*** (0.016)
Constant	-0.245 (0.188)	0.432** (0.199)	
Class share	0.480	0.293	0.228
Observations	8864		
Number of respondents	554		
LL	-1803.912		

***p <0.01, **p <0.05, *p <0.10. Standard errors are in parentheses.

Table 10 presents the estimated WTA and 95% confidence intervals. The WTA estimates derived from the MXL II model are \$3,067.57 for a potential stroke risk, \$4,138.16 for lung cancer risk, \$2,677.89 for coronary heart disease risk, and \$28,939.14 for emotional distress risk. Comparing the estimates of the three classes in the latent class model, the WTA are \$6,410.28, \$1,912.11, and \$2,606.68 for stroke risk; \$4,809.25, \$668.09, and \$18,606.71 for lung cancer risk; \$5,114.62, \$515.28, and \$2,822.96 for coronary heart disease; \$60,766.10 and \$13,210.01 for emotional distress, respectively.

Regarding the U.K. results presented in Table 10, we estimate the WTA of class 3 only because the tax coefficient is either not in line with theory or not statistically significant in other classes. The WTA is \$3,424.69 for stroke risk and \$12,731.80 for lung cancer risk.

Table 9: Willingness to Accept (U.S.)

	CL	G-MNL	MXL I	MXL II	MXL III	Class 1	Class 2	Class 3
Variable	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)
Stroke risk	3496.92 (1393.98-5599.85)	3806.13 (1117.19-6495.08)	2944.55 (1479.60-4409.50)	3067.57 (1591.83-4543.32)	3661.52 (1395.70-5927.35)	6410.28 (2809.77-10010.79)	1912.11 (465.26-3358.96)	2606.68 (220.09-4993.27)
Lung cancer risk	4399.07 (1750.21-7047.92)	6457.12 (1636.47-11277.75)	4184.77 (2174.05-6195.50)	4138.16 (2161.25-6115.07)	5277.55 (2057.80-8497.30)	4809.25 (1972.04-7646.46)	668.09 (35.82-1300.36)	18606.71 (2498.99-39712.41)
Coronary heart disease risk	2842.71 (1136.42-4548.99)	4065.88 (931.67-7200.09)	2706.06 (1393.83-4018.28)	2677.89 (1400.47-3955.31)	3783.85 (1461.05-6106.65)	5114.62 (2280.57-7948.67)	515.28 (77.26-1107.83)	2822.96 (39.41-5685.33)
Emotional distress risk	39271.49 (13687.92-64855.05)	46936.86 (10947.33-82926.40)	30419.28 (14221.10-46617.46)	28939.14 (13632.80-44245.47)	33645.82 (10159.78-57131.85)	60766.10 (18568.02-102964.20)	13210.01 (2247.68-24172.33)	DNA

Note: 95% confidence interval in parentheses was simulated through the Delta method. DNA means does not exist because the estimate is not statistically significant. The coefficients, which were derived by multiplying the WTA formula by the respondents' average monthly health insurance premiums, are in US$.

Table 10: Latent Class: Willingness to Accept (U.K.)

	Class 1	Class 2	Class 3
Variable	Coeff. (C.I)	Coeff. (C.I)	Coeff. (C.I)
Stroke risk	DNA	DNA	3424.69 (942.974-5906.40)
Lung cancer risk	DNA	DNA	12731.8 (6536.89-18926.7)
Coronary heart disease risk	DNA	DNA	DNA
Emotional distress risk	DNA	DNA	DNA

Note: 95% confidence interval in parentheses was simulated through the Delta method. DNA means does not exist. The coefficients, which were derived by multiplying the WTA formula by the respondents' average monthly tax are in USD at £/1.37USD.

3.5 Results from CV Data

Diagnostic tests reveal that the distribution of WTP skewed to the left, and using it at levels can lead to biased predictions because it forces the effects of the independent variables to be additive (Cameron and Trivedi, 2010). Thus, we conduct the Box-Cox specification test on the log of WTP. The test favors the log-linear specification. We further test the functional form of the conditional mean of ln(WTP) using the Ramsey RESET test. We do not reject the null hypothesis that the conditional mean of ln(WTP) is correctly specified. Although the standard errors are specified as robust, we formally test for the presence of heteroskedasticity using the Breusch-Pagan/Cook-Weisberg test. Again, we do not reject the null hypothesis of homoskedasticity.

We conduct robustness checks using quantile regression (median regression). We further estimate a two-part model (or the so-called double hurdle model), but most of the coefficients are not statistically different from zero; thus, we do not present the results.

We pooled the U.S. and U.K. data and estimate the difference using a dummy variable and further estimate separate models using country-specific data. The coefficient of the dummy variable in Table 11 is positive and statistically significant. This shows that U.S. respondents value SHS health risks more than their U.K. counterparts. In both countries, WTP declines with female respondents. Suspecting that the income effects might be responsible for this, we interact income with gender, but it is consistently negative and insignificant. The results are presented in Table A4. U.S. respondents who are living with a partner or spouse value SHS health risks less. However, those whose partner/spouse smokes in both countries are willing to pay more to prevent further SHS exposure. U.K. respondents suffering from or have experienced a serious ill-health are willing to pay more to avert SHS exposure. Also, U.K. respondents exposed to SHS at home/vehicle and are distressed by it value it more than their counterparts. In terms of knowledge, only U.S. respondents with excellent knowledge about SHS health effects are willing to pay more to prevent exposure. Furthermore, income is a significant predictor of WTP.

Table 11: OLS and Tobit Models Estimates (dep. var: ln(WTP))

	Pooled		U.S.		U.K.	
Variable	OLS	Tobit	OLS	Tobit	OLS	Tobit
Dummy†	0.503*** (0.136)	0.499*** (0.133)				
Male	0.622*** (0.122)	0.615*** (0.123)	0.412** (0.180)	0.402** (0.183)	0.832*** (0.163)	0.827*** (0.163)
Living with partner	-0.342*** (0.130)	-0.347*** (0.130)	-0.538*** (0.194)	-0.558*** (0.198)	-0.166 (0.180)	-0.157 (0.167)
Partner smokes	1.099*** (0.259)	1.104*** (0.286)	1.123** (0.556)	1.146** (0.507)	1.169*** (0.249)	1.162*** (0.332)
Health status	0.073 (0.125)	0.076 (0.124)	-0.238 (0.192)	-0.222 (0.189)	0.374** (0.160)	0.366** (0.158)
Exposure place×distress	0.573** (0.232)	0.577** (0.222)	0.397 (0.397)	0.495 (0.361)	0.791*** (0.301)	0.792*** (0.277)
SHS knowledge: Good	0.056 (0.141)	0.045 (0.142)	0.360 (0.224)	0.345 (0.228)	-0.190 (0.179)	-0.203 (0.174)
SHS knowledge: Excellent	0.106 (0.203)	0.086 (0.195)	0.573* (0.305)	0.552* (0.290)	-0.289 (0.251)	-0.304 (0.261)
Income: $1100-$5600	0.232 (0.152)	0.224 (0.157)	0.379 (0.259)	0.344 (0.275)	0.054 (0.186)	0.061 (0.182)
Income: $5601-$10100	0.503* (0.296)	0.481* (0.269)	0.665* (0.353)	0.634* (0.352)	1.422 (0.896)	1.427* (0.753)
Income: More than $10100	0.873** (0.338)	0.869*** (0.329)	1.246*** (0.408)	1.226*** (0.432)	-0.117 (0.559)	-0.109 (0.633)
Constant	3.333*** (0.210)	3.349*** (0.223)	3.893*** (0.334)	3.928*** (0.301)	3.196*** (0.265)	3.201*** (0.268)
sigma		2.614 (0.138)		2.937 (0.221)		2.143 (0.159)
Log-likelihood		-1378.003		-709.256		-653.394
R-squared	0.122	0.032	0.093	0.023	0.144	0.042
Obs.	727	727	364	364	363	363

Note: ***p <0.01, **p <0.05, *p <0.10. Standard errors (in parentheses) are robust. † =1 if U.S. and 0 if U.K. The tobit model is left and right-censored.

Table 12 presents the results of the quantile or median regression, using the 50th and 75th percentiles. It is worthy of note here that the gender discrepancy still holds in both countries. Thus, it is sufficient to conclude that female respondents value SHS risks less than men. In most cases, the signs of the coefficients are not different from those in Table 11.

Table 12: Quantile Regression Model Estimates

	U.S.		U.K.	
Variable	Q(.50)	Q(.75)	Q(.50)	Q(.75)
Gender	0.536*** (0.151)	0.523** (0.247)	0.733*** (0.204)	0.733*** (0.129)
Living with partner	-0.313* (0.169)	-0.523** (0.249)	-0.182 (0.225)	-
Partner smokes	0.562 (0.871)	1.347*** (0.294)	1.057*** (0.291)	0.693*** (0.224)
Health status	-0.156 (0.151)	-0.562** (0.226)	0.510** (0.205)	0.111 (0.132)
Exposure place×distress	0.941*** (0.320)	0.562 (0.478)	0.952*** (0.337)	0.763** (0.325)
SHS knowledge: Good	0.156 (0.171)	0.392 (0.254)	-0.405* (0.233)	-0.223 (0.222)
SHS knowledge: Excellent	0.156 (0.226)	0.036 (0.324)	-	-0.293 (0.208)
Income: $1100-$5600	0.536*** (0.189)	0.379 (0.501)	0.146 (0.211)	0.182 (0.223)
Income: $5601-$10100	0.693** (0.300)	0.680 (0.632)	1.427* (1.427)	1.457 (2.041)
Income: More than $10100	1.22*** (0.452)	1.427*** (0.529)	0.551 (0.979)	0.111 (0.911)
Constant	3.532*** (0.224)	4.748*** (0.545)	3.022*** (0.325)	4.226*** (0.325)
R-squared	0.031	0.069	0.098	0.062
Obs.	364	364	363	363

Note: ***p <0.01, **p <0.05, *p <0.10. Standard errors (in parentheses) are robust.

We present the mean and median WTP of respondents in Table 13. U.S. respondents are willing to pay \$521.63 to prevent SHS exposure compared to \$242.96 by U.K. respondents. The difference is statistically significant ($p < 0.01$). The median WTP is \$100 compared to \$68.57.

Table 13: Willingness to Pay (U.S. & U.K.)

	Mean	Median	Obs.
U.S.	\$521.63 (1861.92)	\$100.00	364
U.K.	\$242.96 (1516.98)	\$68.57	363

Note: Standard deviations are in parentheses.

4 Discussion

Some insights emerge from our results. In Table 6, we find that the coefficient of tax reduction is not significant, indicating that U.K respondents are indifferent to a potential policy that would guarantee an increase in disposable income (monetary payoffs) as compensation for exposure to SHS, but the reverse is the case for U.S. respondents. It could be because the U.K. healthcare system is publicly-funded. In a valuation study on preferences for cancer testing, Hollinghurst *et al.* (2016) concluded that more research was needed to understand how U.K. participants perceive risks because the authors found inconsistent responses.

Another possible reason why there are cross-country discrepancies is the argument about altruism, warm glow, and social preferences. In this context, while it may be difficult for an American to internalize social preferences, it is different for a British. Bridges *et al.* (2003) linked social preferences to social capital, where individuals share a sense of collectiveness or community instead of individualism. Furthermore, it could be that U.K. respondents favor mitigation over compensation (see Knetsch, 1990). As already shown, more British than Americans favor a ban on smoking in private places with a nonsmoker present.

However, sorting the individuals into three distinct classes in Table 8 provides further insights. Generally, the results suggest that they are three segments of respondents with distinct preferences for SHS attributes. The results show a segment of the U.K. population that places a monetary value on stroke and lung cancer risks. Although living in the U.K., these could be individuals having private health insurance or those not registered to a General Practice (GP); thus, they rely on out-of-pocket payments to access healthcare services. Alternatively, it could be that the majority of respondents exposed to SHS in private places belong to this class. Furthermore, it could be that this group is made up of migrants who usually pay for immigration health surcharge in addition to taxes in the U.K. Other studies (Adamowicz *et al.*, 2011; Andersson *et al.*, 2016) have reported similar class distinctions in respondents' valuation of cancer disease attributes.

Valuing a possible attribute - emotional distress, which is lacking in the health valuation literature, provides a novel insight. Bridges *et al.* (2003) argued that including possible attributes in choice experiments leads to a better inference. Our results in Table 9 show that Americans value emotional distress more than other attributes regardless of the group they belong. It is not clear why they put a very high monetary value on this relative to other attributes. However, the American Psychiatric Association (APA) has shown that mental illness is a serious problem in the U.S. as about one in five adults suffer from some form of it (APA, 2018).

Concerning the CV results presented in Table 11, Americans are willing to pay more than their British counterparts. It could be that agents in a private healthcare system like the U.S. are more health "risk-averse" than individuals in a publicly-funded healthcare system, who are certain about receiving free medical services. Other studies have shown that more risk-averse agents have greater WTP to prevent health risks (Fuchs and Zeckhauser, 1987; Liu *et al.*, 1997; Congress, 1997; Smith *et al.*, 2004; Eeckhoudt and Hammitt, 2004).

Another interesting finding is the gender difference, which is consistent in both countries. Our results show that male respondents are willing to pay more than their female counterparts. This suggests that men are more health "risk-averse" than women. The results are mixed in the valuation literature. While some findings are consistent with ours (Frew *et al.*, 2001; Adamowicz *et al.*, 2011; Neumann *et al.*, 2012; Tubeuf *et al.*, 2015), others contradict it (Viscusi and Huber, 2012; Condliffe and Fiorentino, 2014; Andersson *et al.*, 2015).

Respondents with a smoker partner/spouse are willing to pay more. This is not surprising as studies have shown that a nonsmoker with a smoker partner/spouse has a 30% higher risk of developing lung cancer than their counterparts with a nonsmoking partner/spouse (Hirayama, 1984; Pressman, 1993).

Also, we find that U.K. respondents who have experience with some form of serious ill-health have a higher value than their counterparts. This is plausible as experience is the best teacher. They are willing to pay more to avoid further risks of ill-health. Other studies have reported similar findings (Frew *et al.*, 2001; Hammitt and Zhou, 2006; Andersson *et al.*, 2015).

Likewise, respondents exposed to SHS at home and private vehicles are willing to pay more to avoid it. However, the U.S. result is not significant. This could be because 35% of U.K. respondents are exposed in those places compared to only 16% of U.S. respondents. It is also worth mentioning that although smoking prevalence is higher in the U.S, SHS exposure is more in the U.K.

U.S. respondents with excellent knowledge about SHS health effects are willing to pay more. Likewise, Kenkel (1991) found that health knowledge decreases health-risk behaviors among Americans. Furthermore, wealthier respondents are willing to pay more because they have more to lose when they are afflicted with diseases (see also Eeckhoudt and Hammitt, 2004; Adamowicz *et al.*, 2011; Viscusi and Huber, 2012; Andersson *et al.*, 2015, 2019).

From Table 13, U.S. respondents are willing to pay twice more than their U.K. counterparts. The U.S. respondents' mean WTP is greater than the $494 American smokers were willing to pay to avoid their child's exposure to SHS annually (see Agee *et al.*, 2001). It is also higher than the CAN$100 and CAN$225 Canadians were willing to pay to reduce respiratory and cardiovascular diseases reported by Johnson *et al.* (2000). However, Chinese valued chronic bronchitis risks due to air pollution between $500 and $1000 (Hammitt and Zhou, 2006), and $1,711-$2,717 for asthma (Peng and Tian, 2003; Guo *et al.*, 2006).

It is noteworthy that U.S. respondents engage in less risky behaviors relative to their U.K.

counterparts, probably due to their impact on patients' health insurance premiums or out-of-pocket spending, just as people with car insurance are careful not to record an accident. Thus, there is a moral hazard in a publicly-funded healthcare system. It is also important to note that 13% of those exposed to SHS at home/vehicle in the U.K. indicated that their exposure increased during the COVID-19 lockdown. This is consistent with the findings of recent studies conducted in the U.K. (ASH, 2020; Yach, 2020).

5 Conclusion

This study reveals novel findings of how agents in private and publicly funded healthcare systems differ in their valuation of a negative externality like secondhand tobacco smoke health risks. As per the WTP-WTA dichotomy, our results are consistent with Hanemann (1991) and Shogren *et al.* (1994), who showed that in a matter of life, WTA outstrips WTP.

We find that while Americans are positive towards a potential policy that offers a monetary payoff for SHS exposure, the British, on average, are indifferent (neutral) to such policy. We also find that Americans are more health "risk-averse" than their British counterparts as they are willing to pay twice more to avoid SHS health risks even though more Brits are exposed to SHS than Americans. Our results also show that men are more health "risk-averse" than women, and the income effect is not responsible for this finding.

Despite these findings, we recommend that future studies value other environmental hazards such as industrial air pollution, comparing heterogeneous healthcare systems.

Acknowledgements

This study was funded by the University of Exeter, U.K.
The author is grateful to his kind and supportive supervisors, Professor Surajeet Chakravarty and Prof. Brit Grosskopf. He also thanks the following for answering his questions, although they have never met in the flesh: Prof. Arne Risa Hole and Prof. Sylvain Weber.

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A Appendix

Table A1: Summary Statistics of Choice Experiment Models (U.S.)

Utility function variables	Description	Mean	Std. Dev.	Min.	Max.	Obs.
Stroke risk	Continuous	17.38	5.566	10	25	8656
Lung cancer risk	Continuous	22.51	11.758	8	38	8656
Coronary heart disease risk	Continuous	20.33	11.473	5	35	8656
Emotional distress risk	Dummy	0.5	0.500	0	1	8656
Health insurance premium	Continuous	14.900	11.224	0	30	8656

Table A2: Summary Statistics of Choice Experiment Models (U.K.)

Utility function variables	Description	Mean	Std. Dev.	Min.	Max.	Obs.
Stroke risk	Continuous	17.34	5.587	10	25	8864
Lung cancer risk	Continuous	22.67	11.724	8	38	8864
Coronary heart disease risk	Continuous	20.31	11.453	5	35	8864
Emotional distress risk	Dummy	0.5	0.500	0	1	8656
Tax	Continuous	14.900	11.224	0	30	8864

We present other summary statistics not used in the models in Table A3.

Table A3: Other Summary Statistics

Variable	Description	Mean (Std. Dev.)		
		Pooled	US	UK
SHS frequency	=1 if ETS exposure is 4 to 7 times a week	0.58 (0.493)	0.45 (0.498)	0.72 (0.450)
SHS COVID-19	=1 if SHS exposure increased during COVID-19 lockdown			0.13 (0.334)
Consume alcohol	=1 if respondent consumes alcohol	0.68 (0.466)	0.56 (0.497)	0.80 (0.401)
Alcohol quantity	=Average glasses of alcohol per week	2.7 (4.278)	2.1 (4.235)	3.4 (4.236)
Age	=Average age in years	32.2 (11.215)	31.4 (10.511)	32.1 (11.839)
High school diploma	=1 if yes	0.18 (0.386)	0.21 (0.411)	0.15 (0.356)
College diploma	=1 if yes	0.44 (0.497)	0.49 (0.500)	0.40 (0.492)
University degree	=1 if yes	0.24 (0.424)	0.24 (0.427)	0.23 (0.422)
Other educ	=1 if yes	0.14 (0.349)	0.06 (0.253)	0.21 (0.411)
Children	=1 if children are living in household	0.33 (0.469)	0.33 (0.472)	0.32 (0.467)
Pet	=1 if respondent owns a pet	0.49 (0.500)	0.55 (0.498)	0.43 (0.496)
Hhold size	=Household size	3.2 (1.446)	3.1 (1.385)	3.2 (1.505)
Employment	=1 if in full employment	0.71 (0.454)	0.73 (0.444)	0.69 (0.463)
Apartment	=1 if living in own apartment	0.54 (0.498)	0.55 (0.498)	0.54 (0.499)
Env group	=1 if respondent belongs to an environmental group	0.06 (0.231)	0.08 (0.267)	0.04 (0.186)
Race	=1 if white	0.72 (0.449)	0.63 (0.629)	0.81 (0.393)

Robustness Checks

The results in Table A4 show that the income effects do not drive the gender difference. As can be seen, interacting gender with income turns out negative and statistically insignificant in most cases.

Table A4: Model Estimates with Interactions

	Pooled Data		US		UK	
Variable	OLS	Tobit	OLS	Tobit	OLS	Tobit
Dummy†	0.504*** (0.136)	0.500*** (0.133)				
Gender	0.912*** (0.272)	0.895*** (0.273)	0.532 (0.470)	0.462 (0.481)	1.323*** (0.339)	1.325*** (0.318)
Exposure place×distress	0.554** (0.233)	0.559** (0.222)	0.378 (0.395)	0.379 (0.362)	0.807*** (0.301)	0.809*** (0.275)
Income: $1100-$5600	0.366** (0.183)	0.353* (0.197)	0.454 (0.358)	0.384 (0.388)	0.238 (0.212)	0.248 (0.213)
Income: $5601-$10100	0.531 (0.425)	0.497 (0.379)	0.598* (0.257)	0.517 (0.501)	1.473*** (0.230)	1.484 (1.473)
Income: More than $10100	1.370*** (0.357)	1.358*** (0.488)	1.746*** (0.470)	1.689** (0.678)	0.631 (0.544)	0.643 (0.672)
Living with partner	-0.333** (0.131)	-0.339*** (0.130)	-0.486*** (0.196)	-0.568*** (0.198)	-0.127 (0.179)	-0.118 (0.167)
Partner smokes	1.081*** (0.257)	1.087*** (0.286)	1.109** (0.550)	1.133** (0.508)	1.172*** (0.247)	1.165*** (0.331)
Health status	0.067 (0.126)	0.070 (0.124)	-0.244 (0.194)	-0.230 (0.189)	0.375** (0.160)	0.367** (0.159)
SHS knowledge: Good	0.043 (0.140)	0.032 (0.142)	0.350 (0.225)	0.345 (0.228)	-0.201 (0.180)	-0.214 (0.173)
SHS knowledge: Excellent	0.106 (0.203)	0.086 (0.195)	0.579* (0.305)	0.560* (0.290)	-0.302 (0.251)	-0.316 (0.259)
Male×income: $1100-$5600	-0.349 (0.309)	-0.338 (0.309)	-0.142 (0.518)	-0.074 (0.533)	-0.625 (0.386)	-0.635* (0.372)
Male×income: $5601-$10100	-0.156 (0.572)	-0.132 (0.507)	-0.133 (0.711)	0.212 (0.673)	-0.363 (1.220)	-0.376 (1.715)
Male×income: More than $10100	-0.948 (0.608)	-0.929 (0.646)	-0.787 (0.725)	-0.714 (0.861)	-2.348*** (0.770)	-2.361* (1.310)
Constant	3.247*** (0.222)	3.266*** (0.238)	3.857*** (0.402)	3.920*** (0.426)	3.034*** (0.276)	3.036*** (0.282)
sigma		2.604 (0.138)		2.927 (0.221)		2.113 (0.157)
Log-likelihood		-1376.7218		-712.1583		-650.842
R-squared	0.125	0.033	0.096	0.024	0.155	0.045
Obs.	727	727	364	364	363	363

Note: ***p <0.01, **p <0.05, *p <0.10. Standard errors (in parentheses) are robust. † =1 if US and 0 if UK. The tobit model is left and right-censored.

The proportion of zero responses are presented in Table A5. About 33% of U.S. respondents gave zero relative to 34% of U.K. respondents. We treat this as a protest because most respondents said they are unwilling to pay for others' risky behaviors. We asked those that gave a positive value to indicate how sure they were to pay the stated amount in reality. It can be seen that 13.49% of U.S. respondents compared to 15.52% of U.K. respondents are not sure, 22.37% against 27.26% are sure, and 14.97% compared to 22.74% are very sure to pay. Still, in this last category, U.S. respondents are willing to pay $864.07 compared to $131 indicated by their counterparts.

Table A5: WTP by Segment (U.S. & U.K.)

	U.S.		U.K.	
	Proportion (%)	Mean WTP	Proportion (%)	Mean WTP
Protest	32.72	0	34.48	0
Not sure	13.49	$538.38 (1861.92)	15.52	$405.51 (2949.60)
Sure	22.37	$288.85 (667.09)	27.26	$242.70 (731.84)
Very sure	14.97	$864.07 (3323.28)	22.74	$131 (246.56)
No response*	16.45	$512.71 (1306.85)	-	-

Note: Standard deviations are in parentheses. *No response is a segment of the sample that did not indicate how certain they were to pay the stated WTP.