Assessing the Incorporation of Latent Variables in the Estimation of the Value of a Statistical Life

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Abstract

For many years, the economic literature has recognized the role of attitudes, beliefs, and perceptions in estimating the value of a statistical life (VSL). However, few applications have attempted to include them. This article incorporates the perceived *controllability* and *concern* about traffic and cardiorespiratory risks to estimate VSL using a Hybrid Choice Model (HCM). The HCM allows us to include unobserved heterogeneity and improve behavioral realism explicitly. Using data from a choice experiment conducted in Santiago, Chile, we estimate a VSL of US$ 3.78 million for traffic risks and US$ 2.06 million for cardiorespiratory risks. We found that higher controllability decreases the likelihood that the respondents would be willing to pay for risk reductions in both risks. On the other hand, concern about these risks decreases the willingness to pay for traffic risk reductions but increases it for cardiorespiratory risk reductions.

Keywords: latent variables; hybrid choice model; value of a statistical life; air pollution risk reductions; traffic accident risk reductions.

JEL codes: D91, R41, Q51

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1. INTRODUCTION

In this article, we explore the incorporation of latent variables, such as attitudes, beliefs, and perceptions, in the estimation of the value of a statistical life (VSL) using the hybrid choice modeling (HCM) framework. VSL is usually defined as the tradeoff between an individual's own income and small reductions in their own risk or the willingness to pay (WTP) for reductions in their own risk of premature death (Kniesner & Viscusi, 2019; Robinson, Hammitt, Cecchini, et al., 2019). Our application uses *risk controllability* and *concerns* regarding traffic and cardiorespiratory risks as latent variables.

The VSL has been a relevant component in shaping public policies, including those related to health, traffic security, and the environment (Narain & Sall, 2016; OECD, 2012; Robinson, Hammitt, Cecchini, et al., 2019; USEPA, 2017). It depends on the characteristics of the population (such as income, the reference level of risk, and cultural and demographic variables), the attributes of the risk under analysis (cause of death, latency, future health states, size of the risk change), and people's perceptions and attitudes. Other issues that affect the estimates are sample errors, publication bias, and other methodological decisions (Cameron & DeShazo, 2013; Cropper, Hammitt, & Robinson, 2011; Hammitt, 2020; Kniesner & Viscusi, 2023; Robinson, Hammitt, Aldy, Krupnick, & Baxter, 2010; Viscusi, 2018; Viscusi & Masterman, 2017a).

Therefore, it is common to find differences in VSL estimations between countries or even cities within the same country (Robinson, Hammitt, Cecchini, et al., 2019; Viscusi & Masterman, 2017b). VSL can be estimated using revealed preferences, generally through the hedonic wage model or stated preferences, including contingent valuation and choice experiments (CEs) (Alberini, 2019). In recent decades, CEs have become a common approach to estimate VSL in stated preferences. CEs capture the tradeoff between money and risk by asking people to declare their preferences from a set of alternatives that differ in the combinations of levels of these attributes (Hensher, Rose, & Greene, 2005). We are aware of some criticisms regarding the use of CEs in the valuation of mortality risk reductions (Andersson, Hole, & Svensson, 2016). Nevertheless, our focus is on exploring the incorporation of latent variables in estimating the VSL in the context of stated preferences.

For many years, the economic literature has recognized the role of latent variables (an unobserved or not directly measurable variable (Black, Hashimzade, & Myles, 2012)) in the estimation of VSL, but few applications have attempted to include them. People´s perceptions regarding risks will affect their choices and the estimation of the VSL, affecting the evaluation of anti-terrorism policies (Viscusi, 2009) or policies applied in the COVID-19 pandemic (Hammitt, 2020). Latent variables cannot be observed, so researchers must indirectly infer information about them through questionnaires. Examples of latent variables are risk controllability, fear, anxiety, voluntariness, and concern about hazards. In recent decades, choice modelers have sought to incorporate these attitudes and perceptions into the econometric models to improve behavioral realism (Abou-Zeid & Ben-Akiva, 2014). For instance, individual attitudes toward death risk have been used to shed some light on the relationship between different causes of death and the VSL (Alberini & Ščasný, 2013). Other examples are the analysis of terrorism (Robinson et al., 2010; Viscusi, 2009) and cancer (Viscusi, Huber, & Bell, 2014) as dreaded events. For instance, the latter may be valued differently than less dreaded diseases, albeit the evidence is not conclusive (Kniesner & Viscusi, 2019; USEPA, 2017).

Previous attempts to include latent variables in the estimation of VSL have incorporated them directly as explanatory variables in regression models (Alberini & Ščasný, 2013; Carlsson, Daruvala, & Jaldell, 2010; Chilton, Jones-Lee, Kiraly, Metcalf, & Pang, 2006; Olofsson, Gerdtham, Hultkrantz, & Persson, 2019; Tsuge, Kishimoto, & Takeuchi, 2005; Vassanadumrongdee & Matsuoka, 2005). However, McFadden (1986), Ashok, Dillon, and Yuan (2002), Morikawa, Ben-Akiva, and McFadden (2002), and Hess and Beharry-Borg (2012) note that the direct incorporation of latent variables into the definitions of the regression analysis may generate multicollinearity, little predictive validity, and measurement error. Recently, Daziano and Rizzi (2015) and González et al. (2018) suggested including latent variables in the estimation of VSL using the HCM approach. Closely related, Jin, Andersson, and Zhang (2020) estimate an HCM to understand self-protection in the context of valuation for risk reductions in China but did not estimate VSL using this approach. This paper fills this gap by including two latent variables in assessing the VSL using the HCM.

The use of HCM provides the capacity to explicitly model unobserved heterogeneity, improve the behavioral realism of the model, enhance the model efficiency due to the incorporation of more information about latent variables and increase the accuracy of predictions, and could help to design more effective policies related to risk reduction (Abou-Zeid & Ben-Akiva, 2014; Vij & Walker, 2016). For a comprehensive review of the use of HCM, refer to Kim, Rasouli, and Timmermans (2014), and Bouscasse (2018)[1].

Despite their benefits, the HCM is not exempt from some criticisms. Chorus and Kroesen (2014) argued that it is incorrect to extract policy implications from the use of HCM due to the cross-sectional and endogenous nature of latent variables. In the case of the latter, Vij and Walker (2016) pointed out that endogeneity is also a problem with observable variables and that some latent variables are less likely to suffer from endogeneity (e.g., social norms).

[1] These reviews focus on travel choice behavior and mode choice, respectively.

We contribute to the literature in at least three ways. First, we are one of the first studies incorporating latent variables to estimate VSL using the HCM framework[2]. Our application uses two attribute-specific latent variables: *risk controllability* and *concerns* regarding traffic and cardiorespiratory risks. We are interested in these variables because the literature has highlighted their influence on WTP (Haddak, Lefèvre, & Havet, 2016; Jones-Lee & Loomes, 1995). Regarding *controllability*, there is evidence that some individuals believe they control risk more efficiently than others, known as superiority illusion bias (Klein & Kunda, 1994). Regarding concern, although individuals periodically see or read about accidents, some people perceive them as external and are not concerned about risks with a very low probability of occurrence. On the other hand, excessive concern about hazards could affect someone's lifetime productivity (Slovic, Fischhoff, & Lichtenstein, 1978). Second, we add new insights into the relationship between psychological traits such as controllability or concern with perceived risk. Third, we contribute to the scarce literature on the estimation of VSL using CEs that distinguish between different kinds of risks.

The remainder of this article is organized as follows: In the second section, we present the material and methods, including a description of the data collection process and a condensed description of HCM and VSL methodologies. Then, we present and discuss our results and compare them with other VSL estimations in the literature. Finally, we summarize the main findings and limitations in the conclusions.

[2] While this paper was under review, a new article was published using the same original database (Soto, Rizzi, & de Dios Ortúzar, 2023). This article focuses on the influence of survey engagement (i.e., Attribute non-attendance) on the valuation for risk reductions. They did not explore the effect of controllability or concern in the VSL estimation.

2. MATERIAL AND METHODS

2.1 Data collection and choice experiment

We use data from the Chilean Ministry of the Environment collected by the project "*Estimating the value of statistical life associated with atmospheric pollution and traffic accidents*" implemented by GreenLabUC (2014). Using a CE, this study aimed to estimate the WTP to reduce air pollution and traffic risks in Chile. The survey was conducted in Santiago, Chile, in 2014. The interviews were conducted face-to-face in households selected by a stratified probabilistic sampling design. The interviewees were between 25 and 80 years old and lived in urban zones from 34 counties of Region Metropolitana. The original sample has 1,125 individuals.

The research team used four focus groups (23 individuals in the aggregate) and three pilot surveys (n = 18, 42, and 42, respectively) to prepare the questionnaire's final version. In the focus groups, interviewers asked open questions to evaluate the understanding of concepts such as risks, concern, and probability. They also test how individuals interpret and understand the explanatory figures about risk reductions and the CE and their perceptions about traffic and cardiorespiratory risks. The pilot surveys evaluated response rate, survey duration, understanding degree of questions, enumerator's profile, among others. The survey has four sections. First, an introduction with questions to stratify the sample and to know the preferred transport mode. Second, a training section in probabilities aiming at improving respondents' understanding of small risks and the CE exercise. The third section includes questions about perceptions of traffic and cardiorespiratory risks. The final section gathers respondents' sociodemographic information.

The CE has four attributes: reduction of traffic risks, reduction of current cardiorespiratory risk, reduction of future cardiorespiratory risk, and a cost attribute for each alternative. The risk reduction levels vary along with three age groups (25-44, 45-64, and over 65 years old) because their baseline risks are different (Alberini, Cropper, Krupnick, & Simon, 2004; Aldy & Viscusi, 2008). Figure 1 summarizes the attributes and their different levels by age group. The baseline risks were calculated regarding the whole Santiago's population; for instance, individuals between 25 and 44 years old faced a baseline mortality risk for traffic accidents of 200 in 1,900,000, corresponding to the population in that age group in Santiago in 2014. The CE was presented as a public program (supported by new taxes) to reduce traffic and air pollution risks. The program includes: 1) improving traffic routes design, 2) establishing a monitoring driving system, 3) educational programs for drivers and pedestrians, and 4) stricter requirements to obtain and use a driver's license. On the other hand, to reduce the risks of cardiorespiratory diseases associated with air pollution, the program includes: 5) establishing restrictions to industrial pollutant emissions, 6) establishing limits to the usage of pollutant vehicles, 7) incentivizing the development of environmentally friendly technologies, and 8) establishing restrictions to the usage of pollutant fuels and heating appliances with high emissions. Moreover, the risks reductions were presented in yearly terms and will be experienced immediately until their 65th birthday, in which case they will face different baseline risks.

An efficient design (Hensher et al., 2005) was used to obtain nine choice sets with three alternatives, including a status quo alternative (alternative A) and two alternatives with reduced risks relative to the status quo (alternative B and C). An example of a choice situation is presented in figure 2.

[Figure 1 here]

[Figure 2 here]

A set of questions regarding the respondent's concerns and controllability about risks were included in the survey to measure the latent variables. They were six questions related to traffic accidents[3] (associated with the transport mode more used by the interviewee, which could be lightweight vehicle driver, public transport heavy vehicle driver, lightweight vehicle passenger, public transport user, or bicycle) and five questions related to cardiorespiratory risks. These questions used Likert scales with values between 1 and 5, where 1 is no control or concern, and 5 is very concerned or high controllability. We present the descriptive statistics of these items in Table 1.

We use factor analysis to discover the main attitudinal factors from the Likert scale questions[4]. To explain the variance of the data, we use varimax rotation (Fabrigar & Wegener, 2011). Using four main factors, we can explain 56% of the data's variance; these factors and their factor loadings are presented in table 2. The factor loadings represent the correlation between indicators and factors, whose values near 1 or -1 imply a stronger influence of the loading to the factor. The first and second factors represent the *perceived controllability* and *concern about traffic risks*, respectively, and the third and fourth factors describe *perceived controllability* and *concern about cardiorespiratory disease risks* related to air pollution. Note that the items related to concern have a stronger positive preference than those related to control.

[Table 1 here]

[Table 2 here]

[3] The survey also contains four attitudinal questions about traffic accidents for pedestrian.
[4] We used the R function "factanal" to conduct the factor analysis. For further information about factor analysis you can refer to Kline (2014).

Some observations were not included in the estimation because individuals did not provide complete answers to attitudinal questions or the CE exercise. Others were not included because they mentioned that their main transport mode is walking, then they did not face the attitudinal questions related to traffic accidents. Hence, our final sample consisted of 758 individuals.

We use the following explanatory variables: *Traffic accident* is a dichotomic variable taking the value of 1 if the individual had a traffic accident in the last three years and 0 otherwise. Similarly, the variable *Cardiorespiratory disease* takes the value of 1 if the individual had a cardiorespiratory disease and 0 otherwise. *Gender* is a binary variable representing 1 for males and 0 for females. *Education 2* and *Education 3* are binary variables capturing the individual's educational level. *Education 2* denotes secondary education, and *Education 3* tertiary education. The descriptive statistics of these variables are presented in table 3, where the second column summarizes the sample statistics used for analysis, and the third column is for the full sample. By comparing the two samples, we can conclude that they are similar and that the subsampling does not modify the sample's socioeconomic characteristics.

[Table 3 here]

2.2 Hybrid Choice Model specification

HCM is an extension of the classical choice model, which has become the standard framework for including latent variables in choice models.[5] Figure 3, suggested by Walker and Ben-Akiva (2002), depicts the choice modeling framework's main elements. The elements in rectangles are observable, and those in ellipses are unobservable. In the center, we observe the

[5] One of the first proposals to incorporate attitudinal variables in the DCM context is McFadden (1986) but since the work by McFadden (2001) and Ben-Akiva, McFadden, et al. (2002), the literature has showed systematic advances in the estimation of HCM with a high concentration in the area of transportation (Daly, Hess, Patruni, Potoglou, & Rohr, 2012)

(latent) utility level perceived by an individual associated with their choice. This utility depends on the observable explanatory variables, including individuals' characteristics and attributes of the alternatives (superior rectangle) and disturbances reflecting researcher ignorance and individual heterogeneity. These two components are the main elements of the standard (classical) discrete choice model. On the right side, the figure shows the latent variables representing attitudes, beliefs, or perceptions. These variables also depend on a set of individual attributes and disturbances. Since these variables cannot be directly observed, researchers use indirect approaches to measure these variables, called indicators. Past attempts to include latent variables in choice models had assumed that indicators are a direct measure of attitudes and included them directly in the utility function as an observable variable (Hess & Beharry-Borg, 2012). Table 1 and table 2 present the list of indicators measured through Likert scales for our study.

[Figure 3 here]

The latent variables are linked to explanatory variables through a *structural model*; these explanatory variables are usually sociodemographic variables at an individual level but can also be any other type of variable (Kamargianni, Ben-Akiva, & Polydoropoulou, 2014). The latent variables and their structural relationship with individuals´ characteristics can be written as[6]:

$$\delta_{inr} = \sum_{q} \theta_{iqr} z_{inq} + \mu_{inr} \tag{1}$$

Where δ_{inr} is the *r-th* latent variable ($r = 1, \ldots, R$), the subscript *n* identifies individuals ($n = 1, \ldots, N$) and the i denotes the chosen alternative from the choice set ($i = 1, \ldots, J$). The latent variables are linked to a set of q explanatory (sociodemographics) variables denoted by z_{inq}. In

[6] We based our model formulation on Soto, Márquez, and Macea (2018).

this structural model, θ are the parameters to be estimated and μ_{inr} are normally distributed disturbances with mean zero and variance-covariance matrix Ψ. A common practice in HCMs is to use a unitary fixed value at Ψ to ensure the identification of the parameters; nevertheless, extensive discussions of other options for identification are offered by Raveau, Yáñez, and Ortúzar (2012), Daly et al. (2012), and Vij and Walker (2014), among others.

Since latent variables are unobservable, we need to link them to the indicators through a *measurement model*. The measurement model may have different specifications. Three possible formulations for the indicators are the continuous, binary, and ordered models (Bolduc & Alvarez-Daziano, 2010; Daly et al., 2012). Since the Likert scale has five levels, the measurement equation follows an ordered indicator L_{inp} with K levels and a set of τ threshold parameters. Equation 2 and 3 present the relationship between each $\mathrm{L_{inp}}$ indicator and latent variables:

$$\mathrm{L_{inp}} = \begin{cases} 1 \;\; if \; \tau_0 \leq \; L^*_{inp} \leq \tau_1 \\ 2 \;\; if \; \tau_1 \leq \; L^*_{inp} \leq \tau_2 \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ K \; if \;\; \tau_{K-1} \leq \; L^*_{inp} \leq \tau_K \end{cases} \tag{2}$$

$$\mathrm{L^*_{inp}} = \sum_{\mathrm{r}} \mathrm{\gamma_{ipr}\delta_{inr}} + \mathrm{\zeta_{inp}} \tag{3}$$

Usually, it is assumed that $\tau_0 = -\infty$ and $\tau_K = \infty$, and γ_{ipr} is a vector of unknown parameters that associate the latent variable with the indicators and ζ_{inp} is a vector of error terms that could vary according to the assumptions about the relationship across indicators. In other words, in response to the attitudinal questions, an individual will reflect their genuine latent variable (δ_{inr}) in the level assigned to the Likert scale L_{inp}.

In the measurement model, 22 indicators (Likert questions) were used to identify the latent variables. Following table 1 and table 2, indicators L_1, L_2, L_3, L_4, L_5 and L_6 are used for *controllability of traffic accidents* (δ_1); for *concern about traffic accidents* (δ_2), we used indicators $L_7, L_8, L_9, L_{10}, L_{11}$ and L_{12}; for *controllability cardiorespiratory disease risk* (δ_3), we used indicators $L_{13}, L_{14}, L_{15}, L_{16}$, and L_{17}; and finally, indicators $L_{18}, L_{19}, L_{20}, L_{21}$, and L_{22} were used for *concern about cardiorespiratory disease risk* (δ_4).

Assuming independence among indicators and that the measurement model is an ordered logit, then the probability of observing L_{inp} within a level *k* can be written as equation 4:

$$\mathbf{P(L_{inp} \in k \mid \boldsymbol{\delta}_n) = \frac{1}{1 + e^{-(\boldsymbol{\tau}_{pk} - \sum_r \boldsymbol{\gamma}_{ipr} \boldsymbol{\delta}_{inr})}} - \frac{1}{1 + e^{-(\boldsymbol{\tau}_{p(k-1)} - \sum_r \boldsymbol{\gamma}_{ipr} \boldsymbol{\delta}_{inr})}}} \tag{4}$$

Regarding latent variables in the indirect utility function, they can be incorporated in several ways, depending on their nature and the researcher's interest. In our case, *controllability* and *concern about risk are* "attribute specific" latent variables. Therefore, they were interacted with their respective attributes in the definition of the utility function. This definition is presented in equation 5 for a linearly additive indirect utility function (U_{in}):

$$U_{in} = ASC_i + \sum_t \beta_{it} X_{int} + \sum_t \sum_r \alpha_{irt} X_{int} \delta_{inr} + \varepsilon_{in} \tag{5}$$

ASC_i is the alternative-specific constant, which in our case will be estimated only for the status quo alternative, X_{int} are the *t* attributes presented in the CE, β_{it} and α_{irt} are parameters associated with the attributes and their latent variables respectively. Finally, ε_{in} is an independent and identically distributed extreme value type I disturbance term. Our specification is the following:

$$\begin{aligned}
&\mathbf{U_1 = ASC_1 + \beta_1 * traffic_1 + \alpha_1 * traffic_1 * \delta_1 + \alpha_2 * traffic_1 * \delta_2 + \beta_2 * cardio_current_1 +} \\
&\mathbf{\alpha_3 * cardio_current_1 * \delta_3 + \alpha_4 * cardio_current_1 * \delta_4 + \beta_3 * cardio_future_1 + \beta_4 * cost_1 + \varepsilon_1} \\
&\mathbf{U_2 = \beta_1 * traffic_2 + \beta_2 * cardio_current_2 + \beta_3 * cardio_future_2 + \beta_4 * cost_2 + \varepsilon_2} \\
&\mathbf{U_3 = \beta_1 * traffic_3 + \beta_2 * cardio_current_3 + \beta_3 * cardio_future_3 + \beta_4 * cost_3 + \varepsilon_3}
\end{aligned} \tag{6}$$

Where $traffic_i$ is the traffic risk reduction attribute, $cardio\_current_i$ is the current cardiorespiratory risk reduction, $cardio\_future_i$ is the future cardiorespiratory risk reduction, and $cost_i$ is the vector of prices associated with the different *i* alternatives. The model includes the latent variable δ_1 denoting *risk controllability* regarding traffic accidents, δ_2 that reflects the concern about premature deaths in traffic accidents, and δ_3 and δ_4 that represent the risks of controllability and concern about premature death due to a current cardiorespiratory disease.

In the structural model, which contains sociodemographic variables explaining the latent variable, we explored several specifications with different explanatory variables. After removing those not statistical§ly significant variables, we incorporated *Traffic accident*, *Cardiorespiratory disease*, *Gender*, *Education 2*, and *Education 3* as explanatory variables of the four latent variables. Following Hess, Train, and Polak (2006), we used the modified Latin hypercube sampling method to obtain 500 draws for the random components.

As in any choice model, the individual's choices regarding the different alternatives represent the maximum utility among all options (equation 7):

$$y_{in} = \begin{cases} 1 & \text{if } U_{in} > U_{jn} \quad \forall\ i \neq j \\ 0 & \text{Otherwise} \end{cases} \tag{7}$$

Therefore, the choice model's joint probability with the latent variable indicators is obtained by multiplying the conditional probability of the choice by the indicator's conditional density function and integrating over the density of latent variables. That is:

$$\mathbf{P}(\mathbf{y_{in}}, \mathbf{L_n} | \mathbf{x_n}, \mathbf{z_n}, \boldsymbol{\lambda}) = \int_{\boldsymbol{\delta}} \mathbf{P}(\mathbf{y_{in}} | \mathbf{x_n}, \boldsymbol{\delta}_\mathbf{n}, \boldsymbol{\alpha}, \boldsymbol{\beta}) \mathbf{f}(\mathbf{L_n} |\ \boldsymbol{\delta}_\mathbf{n}, \boldsymbol{\gamma}, \boldsymbol{\tau})\, \mathbf{g}(\boldsymbol{\delta}_\mathbf{n} | \mathbf{z_n}, \boldsymbol{\theta}) \mathbf{d}\boldsymbol{\delta}_\mathbf{n} \tag{8}$$

where $\lambda = \theta, \beta, \alpha, \gamma, \tau$ are parameters to be estimated. Estimating the probability of equation (8) requires calculating multiple integrals, so the literature provides different numeric methods and simulations[7]. Several authors have addressed issues affecting the estimation of hybrid choice models (Ashok et al., 2002; Bolduc & Alvarez-Daziano, 2010; Raveau, Álvarez-Daziano, Yáñez, Bolduc, & Ortúzar, 2010). We jointly estimate the choice and latent variable models using the R package Apollo (Hess & Palma, 2019).

Additionally, we estimate multinomial logit models (MNL) as benchmark models. Other authors have used MNL to compare against HCM. For instance, Hess and Beharry-Borg (2012) compared HCM against MNL, arguing that MNL is a departure point of most choice modelling applications. In the main text, we present MNL1, which includes only the attributes shown in the CE, and MNL2, which includes the attitudinal variables interacted with risk reductions to be directly incorporated in the utility function as past studies did. Nevertheless, it is essential to remember that these models are not fully comparable as their flexibility varies among them (Mariel & Meyerhoff, 2016), and the direct incorporation of attitudinal indicators in the utility function

[7] Train (2009) in his book provides a very nice recompilation of the most common methods.

could generate measurement error, endogeneity bias, among other issues (Ben-Akiva, Walker, et al., 2002; Hess & Beharry-Borg, 2012). Finally, we analyzed the validity of our results by using the content, construct, and criterion validity tests framework proposed by Bishop and Boyle (2019), and testing for insensitivity to scope as different guidelines suggest (Narain & Sall, 2016; Robinson, Hammitt, Cecchini, et al., 2019).

3. RESULTS AND DISCUSSION

This section will present the structural (the factors that influence latent variables) and measurement (the relationship between latent variables values and indicators) models in the first place. After that, we will show the choice component results and the estimated WTPs necessary to calculate the VSL. Therefore, the results of the structural (equation 1) and measurement model (equation 2, 3, and 4) are shown in table 4.

Concerning the factors that influence the latent variables, the variable *traffic accident* is statistically significant in the regression of *controllability* and has a positive sign, which implies that the experience of a traffic accident in the last three years increases one's perceived controllability about traffic risks (as it happened one time, it will not happen again). On the other hand, having a *cardiorespiratory disease* in the past negatively impacts the reported concern of these risks. In the case of gender, males feel a higher sense of control related to traffic and cardiorespiratory risks than females and have less concern about these risks. The educational level also plays a role in the perceived control and concern about these risks. In particular, education positively impacts the controllability of traffic risks and concern about cardiorespiratory risks. Finally, education negatively impacts the concern about traffic accidents and the perceived control of cardiorespiratory diseases.

[Table 4 here]

On the other hand, the γ parameters (equation 3) are statistically significant and positive for all the attitudinal indicators. This implies that indicators are positively correlated to latent variables. Furthermore, as we used an ordered logit in the measurement model, we also estimated several threshold parameters. Generally, threshold parameters are statistically significant, which signals that the ordered logit model captures the individual's perceptions and attitudes indicated in the Likert scale questions. However, as these parameters do not provide other helpful interpretations in HCM, we reported them in table B1 in appendix B.

The results of the MNL1, MNL2, and HCM (choice model) are presented in table 5. Although we calculated the WTP (in US$[8]) for reductions in traffic, current, and future cardiorespiratory risks, we focused our analysis only on the former two. We calculate WTP's variance through the delta method and present the log-likelihood of the choice model and the joint model (only for the HCM).

[Table 5 here]

In the benchmarking models, the coefficients of traffic and future cardiorespiratory risks were always statistically significant. The ASC parameter was not statistically significant only in MNL2, and current cardiorespiratory risks were not statistically significant in MNL1 and MNL2. They have the expected negative signs, that is, a higher risk level implies a negative change in the individual's utility. The negative sign in the alternative-specific constant means that choosing the status quo (higher risk) negatively affects utility. In the HCM, the parameters of traffic risk, current and future cardiorespiratory risk, and cost are statistically significant and with the expected negative sign. The alternative-specific constant is statistically significant and has the same

[8] We present the estimated WTP in US$ by using an exchange rate of 1 US$ = 600 chilean pesos.

direction as in MNL. Changes in explanatory variables statistical significance (or signs) are not uncommon when using HCM. Bouscasse (2018) finds these common divergences and suggests that a HCM can detect the true role of the variables.

Concerning the latent variables, we found in MNL2 that most of them were not statistically significant. However, in HCM, we observe that perceived controllability regarding traffic and cardiorespiratory risks are statistically significant and have a positive sign. Notice that these variables are included only in the status quo alternative. Therefore, these signs are consistent with the literature, that is, if people believe that they have more control over the possibility of a traffic accident or a cardiorespiratory disease, they will choose the status quo more often, meaning that they are less likely to pay for a reduction in any risk. We expected a negative sign in the latent variables related to the concern about risks, but this was true only for *concern about cardiorespiratory risks*. Concern about traffic accidents has a positive and statistically significant sign. We conjecture that, unlike cardiorespiratory risks, if an individual is concerned about traffic accidents, they can take actions to reduce this risk. In other words, concern about risk generates different behaviors depending on the risk type. Note that the effect of concern (about traffic and cardiorespiratory risks) is higher than the direct effect of the attribute itself, showing the implications of including latent variables (and the use of HCM) to improve our understanding of people's preferences about risks.

Overall, we found more statistically significant variables in the HCM than in the benchmark models. In past studies using the MNL2 approach, the statistical significance of indicators is mixed. For instance, Carlsson et al. (2010) and Tsuge et al. (2005) did not find statistical significance in controllability, but Olofsson et al. (2019) found statistical significance for some types of risk. We believe that using indicators directly in the utility function could be misleading in VSL studies because they could generate measurement error, endogeneity bias, among other issues (Ben-Akiva, Walker, et al., 2002; Hess & Beharry-Borg, 2012).

Regarding the mean marginal WTP, both benchmark models present values around US$ 0.26 for reductions in the probability of premature death related to traffic risks. The WTP for cardiorespiratory risks was not statistically significant. In the HCM, the mean marginal WTP for a reduction of premature death in traffic risks is US$ 0.2079, with a confidence interval ranging between US$ 0.1272 and US$ 0.2885. The mean marginal WTP for current cardiorespiratory risks is US$ 0.1132, with a confidence interval between US$ 0.0780 and US$ 0.1485. Besides, the WTP for future cardiorespiratory risks is not statistically significant. A higher valuation for traffic risk reductions than for cardiorespiratory risk reductions may be explained, among other reasons, by the underweighting of risks that individuals are directly exposed such as air pollution (Viscusi, 2009).

We aggregate WTP to obtain VSL by multiplying each WTP by 12 (to annualize the value), multiplying by the size of the population in each age group (P_{age}) and multiplying by a weighting rate that represents each n individual in the sample. Then, we aggregate the VSL by summing up VSL_1, VSL_2 and VSL_3.

$$VSL \begin{cases} if\ age\ 25-44: VSL_1 = 12 * P_{age\_1} * WTP_1 * \frac{W_n}{\sum W_n} \\ if\ age\ 45-64: VSL_2 = 12 * P_{age\_2} * WTP_2 * \frac{W_n}{\sum W_n} \\ if\ age > 65: VSL_3 = 12 * P_{age\_3} * WTP_3 * \frac{W_n}{\sum W_n} \end{cases} \tag{9}$$

Table 5 presents the marginal WTPs for reductions in traffic and current and future cardiorespiratory risks estimated by the benchmark models and HCM. Note that these WTPs represent the valuation of reducing one premature death over the relevant Santiago population, and the differences of baseline risks across age groups are adjusted by P_{age}. The population in each age segment in Santiago is 1.9 million individuals for the age range between 25 and 44 years old (P_{age_1}), 1.5 million for the segment aged between 45 and 64 years (P_{age_2}), and 0.6 million for those aged 65+ years (P_{age_3}) (INE, 2014). Table 6 summarizes our estimated VSL for each model with their respective lower and upper bounds, and additionally, in parentheses, we present values in 2019 dollars[9]. For traffic, using MNL models, the VSL is US$ 4.68 million or US$ 4.72 million, depending on the model. When we use HCM, this value decreases to US$ 3.78 million. For reductions in current cardiorespiratory risks, using MNL1 or MNL2, the VSL is not statistically significant, but in the HCM the VSL is US$ 2.06 million. Conversely, for future cardiorespiratory risks, the VSL is not statistically significant in the HCM, but it is in the MNL models, with a value of US$ 0.15 million for MNL1 and US$ 0.08 million for MNL2.

[Table 6 here]

Although the main aim of our article is not to compare VSL values but to assess the incorporation of latent variables in the estimation of VSL, we present a brief comparison of these values with other estimates in the literature. Most recent efforts to estimate VSL for Chile were conducted by Parada-Contzen, Riquelme-Won, and Vasquez-Lavin (2013), Mardones and Riquelme (2018), Parada-Contzen (2019) and Vasquez-Lavin, Bratti, Orrego, and Barrientos (2022), all using

[9] We adjusted the estimates by inflation and real income growth to 2019 US$. For Chilean data, we used World Bank data (https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG), while for the metanalyses, we used the US Consumer Price Index data (https://www.bls.gov/cpi/data.htm). We converted estimates from Chilean pesos to US$ by using official exchange rates published by the World Bank(https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=CL). Next, we used the formula provided by USSHS (2016) to adjust for income over time: $\mathrm{VSL}_{\mathrm{year\ y}} = \mathrm{VSL}_{\mathrm{year\ x}} * (1 + \mathrm{real\ income\ growth\ rate})^{\mathrm{income\ elasticity} * (x-y)}$. For the metanalyses, we used a unitary income elasticity and a fixed real income growth rate of 2.5% following Narain and Sall (2016) guidance. In the case of Chilean VSLs, we used GDP per capita growth World Bank data (https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?locations=CL) and an income elasticity of 0.85, which was suggested by Masterman and Viscusi (2018) for countries with a VSL higher than US$ 2 million.

revealed preference methods and GreenLabUC (2014) using SP. In particular, Parada-Contzen et al. (2013) estimate a VSL of US$ 6.18 million without endogeneity correction and US$ 17.1 million with the correction, Mardones and Riquelme (2018) estimate US$ 0.98 million without endogeneity correction and US$ 3.22 million with the correction, Parada-Contzen (2019) estimate several models using panel data with a range of values between US$ 0.64 million and US$ 9.08 million, and Vasquez-Lavin et al. (2022) used a pseudo-panel approach which produced VSL values between US$ 2.16 million and US$ 3.12 million depending on different estimation strategies and whether the cohort is balanced or not. Moreover, Rizzi and De La Maza (2017) review earlier VSL estimates for Chile. They found a range between US$ 0.23 million and US$ 2.12 million. Their upper value is an estimate from the OECD (2012). This range contains stated preference studies, but it is inappropriate to use them since they were from studies conducted between 1999 and 2002 and used convenience sampling (GreenLabUC, 2014).

In international terms, numerous articles have summarized evidence worldwide and provided guidelines to transfer VSL values from one country to another. For instance, Viscusi and Masterman (2017b) reported values for 189 countries, with a range between US$ 0.053 million and US$ 22.5 million, assigning a mean value of US$ 1.5 million to upper-middle-income countries. Similarly, Robinson, Hammitt, and O'Keeffe (2019) reviewed the VSL studies in countries classified as low- or middle-income countries and provided some VSL estimates adjusted by the gross national income per capita (GNIpc). The estimates for countries similar to Chile (GNIpc around US$ 20,000 in 2014) were between US$ 2.34 million and US$ 3.93 million. Finally, in a recent and comprehensive review of VSL estimates, Keller, Newman, Ortmann, Jorm, and Chambers (2021) estimate a median of US$ 5.7 million which decreases to US$ 5.2 million only considering stated preferences studies. Moreover, when they consider only studies related to transportation safety, the VSL is around US$ 5.3 million, and in the environment sector, it decreases to US$ 1 million.

Another relevant comparison is regarding other studies jointly addressing air pollution and traffic accident risk reductions. For instance, Vassanadumrongdee and Matsuoka (2005) found that Thailand's VSL for reducing air pollution and traffic accident risks are very close. A similar result was found in Alberini and Ščasný (2011), who included respiratory illness, cancer and road traffic accidents as levels of the attribute "cause of death" in a CE conducted in Italy and the Czech Republic and found that the VSL of cancer is significantly higher than for respiratory illness and road traffic accidents, but they are very similar between them. However, using the same data, Alberini and Ščasný (2013) explored the heterogeneity of VSL estimates and found that the predicted VSL in a respiratory illness context is around one million euros higher than for road traffic accidents when controlling by the same factors. A higher valuation for risk reductions related to respiratory diseases than traffic accidents was also found by Tekeşin and Ara (2014) in Turkey.

Therefore, while our VSL estimates for traffic risk reductions are in the upper range of the values estimated for Chile, they are on the global average according to the latest systematic review available (Keller et al., 2021). Regarding VSL for current cardiorespiratory risks, they align with the most recent revealed preference estimates from Vasquez-Lavin et al. (2022) for Chile and also close to the values proposed by Robinson, Hammitt, and O'Keeffe (2019) for countries similar to Chile. Lastly, when we compared our results to other studies estimating the VSL for traffic and cardiorespiratory risks together, we found that traffic VSL is higher than cardiorespiratory VSL, while the previous literature found that both values are similar, or that respiratory VSL is higher than traffic VSL. However, our findings are supported by the systematic review of Keller et al. (2021).

Finally, we performed several validity tests. We mainly followed the framework proposed by Bishop and Boyle (2019) and the recommendations from different guidelines (Narain & Sall, 2016; Robinson, Hammitt, Cecchini, et al., 2019), and we believe that our estimations pass their validity tests. Particularly relevant, we performed internal scope tests, and we passed its weak version consistently, but we were not able to test for external scope sensitivity. In Appendix A, we present further discussion of the benchmark models plus the validity checks of our estimates.

4. CONCLUSIONS

In this article, we estimate the WTP and VSL for the population of Santiago, Chile, including variables that capture the individual's controllability and concern about traffic and cardiorespiratory risks. Using a hybrid choice model, we can make explicit how latent variables affect the preferences for risk reductions. In our application, the effect of concern about cardiorespiratory risks is even higher than the effect of the attribute. Moreover, as Bouscasse (2018) also highlighted, we verify some changes in the statistical significance of some variables when we move from the classical approach to the HCM.

Nevertheless, the estimated VSLs in this study present some limitations. First, the CE was conducted only in Santiago's metropolitan area, representing a relevant share of Chile's population but not the whole country. Many factors could generate differences between Santiago´s population and other regions (e.g., heterogeneous risk reductions valuation, average income, and other cultural factors). We are aware that, during 2023, the Chilean government (through the Ministry of Social

Development) is working on the development of strategies to account for these regional differences in the estimation of the VSL. However, our main objective was to explore the incorporation of latent variables in the estimation of VSL by using the HCM, and we did not attempt to estimate an unbiased and representative VSL value for the country. Second, the baseline risks used in this CE are realistic but very small, for instance, the mortality risks in traffic accidents are 200 out of 1,900,000 for the age group between 25 and 44 years old; this issue might be biasing the VSL upward. Again, we do not claim our estimates have overcome these difficulties, but this is an issue that deserves further research since it is not exclusive to our HCM application.

Additionally, it is necessary to consider that the cost of estimating the HCM is higher than that of conventional models (Mariel & Meyerhoff, 2016). The estimation time ranges from a few seconds in the MNL to many hours/days in HCM. Furthermore, it is necessary to try several starting points to ensure that the estimates are not the product of just one of the many possible local maxima. It is also relevant to test a sufficiently large number of random draws in the structural model since, in our experience, with a low number of draws, the results are volatile. Moreover, the model specification might affect the VSL. We tested several utility specifications and different explanatory variables (such as age groups and sociodemographic status) in the structural model, and we selected the one with the highest explanatory power. In future research, providing a distribution of VSL values for different specifications might be useful. Nevertheless, the high computational time needed to estimate each model is and could be a relevant constraint in future applications.

There are other challenges to address in future research. It would be interesting to incorporate new latent variables such as anxiety, fear, voluntariness, or uncertainty about premature death not only in the estimation of VSL but also in the broad field of how people perceive risk. Moreover, alternative specific latent variables could be used for different types of risk. For instance, Daziano and Rizzi (2015) recommend exploring the estimation of VSL using shocks to a fatality index (introduced as an explanatory variable in the structural model). In addition, researchers could combine approaches such as the one proposed by Cameron and DeShazo (2013) with the HCM used here, to disentangle the effect of risk-related attitudes on different future health states (e.g., controllability may affect differently in pre-illness and post-illness health states). Regarding the policy implications of using HCM, we do not explore this issue further, but some authors recommend being cautious with these implications (Chorus & Kroesen, 2014; García-Melero, Sainz-González, Coto-Millán, & Valencia-Vásquez, 2021).

Finally, despite the increase in the complexity of the estimation process, we conclude that incorporating latent variables into a HCM when a stated preference study is conducted is helpful in explicitly understanding and decomposing unobserved heterogeneity and increasing the behavioral realism of the model. To the best of our knowledge, this is one of the first articles to explicitly incorporate attitudes and perceptions into the estimation of VSL using an HCM framework. We use the most recent stated preferences data collected in Chile and generate further evidence on the relationship between controllability and concern with the valuation of risk reductions.

Appendix A. Benchmark models and validity checks

This appendix explains the benchmark models used to provide a reference point to analyze the HCM results. Other authors have used Multinomial Logit (MNL) models to compare against HCM. For instance, Hess and Beharry-Borg (2012) compared HCM against MNL, arguing that MNL is a departure point of most choice modelling applications. In the main text, we presented MNL1, which includes only the attributes presented in the CE, and MNL2, which includes the attitudinal variables that interacted with risk reductions to be directly incorporated in the utility function as past studies did. This appendix explains how we chose these attitudinal variables and explore further estimations.

The attitudinal variables were on a scale of 1 to 5. We have six indicators for each latent variable in traffic risks and five indicators for each latent variable in cardiorespiratory risks. Therefore, choosing which one to incorporate into the model is tricky. We are going to use the higher factor loadings of table 2 (L_5, L_9, L_{16}, L_{19}) to choose which indicators to use in MNL2. There is no theoretical reason behind the decision; we preferred not to overcomplicate the analysis. However, we also present MNL3, which used the lower factor loadings ($L_1, L_{12}, L_{17}, L_{18}$) to test how the arbitrariness of choosing an indicator influences the sign and statistical significance of the parameters. Another relevant decision is whether to use the indicator as a dichotomous variable or in its continuous form. MNL2 and MNL3 were done using a dichotomous variable with the attitudinal scale (3 or higher takes value 1, and 0 otherwise[10]) as is the most used approach in the previous literature (Alberini & Ščasný, 2013; Olofsson et al., 2019; Tsuge et al., 2005; Vassanadumrongdee & Matsuoka, 2005). Moreover, MNL4 and MNL5 are the estimations using

[10] We tried with 4 or higher, but the results were mostly not statistically significant.

the continuous scale of higher and lower factor loadings, respectively. These estimations are presented in table A1.

Table A1. Estimation results from additional benchmark models.

Explanatory variables	**MNL3 Coefficient (Robust t-ratio)**	**MNL4 Coefficient (Robust t-ratio)**	**MNL5 Coefficient (Robust t-ratio)**
ASC	0.4728 (1.57)	-0.0619 (-0.20)	-0.0906 (-0.22)
Traffic risk	-0.0162 (-7.86)	-0.0155 (-7.64)	-0.0149 (-7.31)
Current cardiorespiratory risk	-0.0007 (-1.05)	-0.0012 (-1.95)	-0.0016 (-2.57)
Future Cardiorespiratory risk	-0.0004 (-3.15)	-0.0003 (-2.63)	-0.0002 (-1.88)
Cost	-0.0001 (-6.56)	-0.0001 (-6.62)	-0.0001 (-6.65)
Traffic Controllability	-0.0013 (-1.544)	-0.0002 (-0.69)	0.0000 (0.02)
Traffic Concern	-0.0034 (-2.47)	-0.0004 (-1.22)	-0.0005 (-1.40)
Cardiorespiratory Controllability	0.0000 (-0.01)	0.0001 (2.03)	0.0001 (2.29)
Cardiorespiratory Concern	0.0000 (-0.24)	0.0000 (-0.63)	0.0000 (-0.59)
Log-likelihood choice model	-7084	-7106	-7102
N	758	758	758

Source: Author's elaboration. WTP values in parentheses are their 95% confidence intervals. WTP standard errors were calculated using the delta method.

In these models, traffic and future cardiorespiratory risks and cost coefficients were always statistically significant. The ASC parameter was not statistically significant, and the current cardiorespiratory risks parameter was statistically significant in MNL4 and MNL5. The statistically significant parameters have the expected negative signs. That is, a higher risk level implies a negative change in the individual's utility.

Regarding the latent variables, traffic concern was the only statistically significant in MNL3 and cardiorespiratory controllability in MNL4 and MNL5. Overall, we found more statistically significant variables in the HCM than in the benchmark models.

To evaluate the validity of our results, we estimated a bunch of models to explore whether our study accomplished “the Three Cs” discussed by Bishop and Boyle (2019): content, construct, and criterion validity. Content validity refers to the suitability of the valuation method and whether the procedure was adequate to estimate the true value. Criterion validity is related to how similar the WTP estimates are to previous estimates using a different and more reliable method for the same or similar good. Finally, construct validity is related to what we can expect of each attribute based on theory. A well-known construct validity measure in VSL literature is the test for scope sensitivity, which we explore below.

Regarding content validity, this study relies on the experiment implemented by GreenLabUC (2014) (supported by the Ministry of Environment), which carefully evaluated the adequacy of different methods to calculate the VSL and conducted several pilot surveys and focus groups on generating a validated questionnaire. GreenLabUC has significant experience in the application of stated preference studies in Chile.

In terms of criterion validity, we compared our findings with the relevant literature in the main text. In particular, when we compare our estimates with revealed preference studies in Chile, we found that although VSL for traffic accidents is in the upper range of the values estimated for Chile, the VSL for cardiorespiratory diseases is in line with the latest study using labor market data (Vasquez-Lavin et al., 2022). Lastly, we tested the construct validity by performing several estimations to explore income effects, the WTP’s proportionality for risk reduction changes (scope test), and to check that every parameter has the expected sign following the economic theory. It is relevant to mention that we performed all these validity checks by estimating MNL models because carrying them out using HCM would be overwhelming in computational terms.

Then, in table A2, we show MNL6, which incorporates an interaction term between household income (measured as a variable between 1 and 10 in which each number represents an increasing income group) and the cost parameter. The estimated parameter is statistically significant and has a positive sign as predicted by the theory. This means that as higher the household income, the individuals are less sensitive to the cost attribute. Besides, GreenLabUC (2014) combined education and occupation information to generate a proxy variable of the socioeconomic status of each household. In MNL 7, we interacted three different levels of socioeconomic status (low, middle, and high) with the cost parameter. As the reference level is the middle socioeconomic group, we found that the low socioeconomic group is more sensitive to the cost parameter than the middle group, and the high socioeconomic group is the opposite.

Table A2. MNL estimations to test income effect.

Explanatory variables	**MNL6 Coefficient (Robust t-ratio)**	**MNL7 Coefficient (Robust t-ratio)**
ASC	-0.2484 (-1.93)	-0.2927 (-2.27)
Traffic risk	-0.0173 (-8.02)	-0.0167 (-7.74)
Current cardiorespiratory risk	-0.00002 (-0.03)	-0.000001 (-0.002)
Future Cardiorespiratory risk	-0.0006 (-3.91)	-0.0005 (-3.66)
Cost	-0.0002 (-4.37)	-0.0001 (-3.27)
Income*Cost	0.00002 (2.12)	-
Socioeconomic High*Cost	-	0.0001 (2.22)
Socioeconomic Middle*Cost		Reference level
Socioeconomic Low*Cost	-	-0.0002 (-2.60)
Log-likelihood choice model	-7129	-7089
N	758	758

Source: Author’s elaboration.

To test the WTP’s proportionality for risk reduction changes, we could interpret the statistical significance and sign of the risk reduction attributes as evidence of its proportionality (Tsuge et al., 2005). (Tsuge et al., 2005). Another approach, also known as the scope test, consists of testing whether the WTP for risk reduction changes as the risk reduction changes. The scope test can be internal (within the individual) or, external (between individuals) and weak (risk parameter higher if the risk reduction is higher), or strong (risk parameter is proportional to the risk reduction increase). We can perform an internal scope test as respondents faced different risks in each choice situation by design. However, we did not have a between-sample design aimed at performing an external scope test because even though we have different samples, their risk reductions were different. We presented different risk reductions depending on the age group (25-44, 45-64, and +65 years old, see Figure 1). We could use this as a proxy of an external scope test. Unfortunately, the differences in risk reduction valuation can be driven by age-specific factors that make this proxy flawed, so we decided not to pursue this approach. Therefore, to perform these tests, we separate the risk attributes into dichotomous variables to estimate specific parameters for each risk reduction. We develop this approach in Table A3. As the size of the risk reductions varies within the age groups, we needed to conduct these estimations by each age group separately. However, the estimation for the older group (+65 years old) did not converge, maybe because of the smaller sample. Therefore, MNL8 estimates the 25-44 years old group and MNL9 with the 45-64 years old group.

In general, we found few statistically significant variables. It is important to mention that the efficient design of this study was carried out using an econometric specification where risk reductions are continuous variables instead of dichotomous; therefore, it could affect the statistical significance we found. In fact, the cost parameter is not statistically significant, which does not allow us to test the proportionality of risk reductions in terms of WTP. Still, we have at least two parameters per risk reduction in each equation, so we can perform a scope test by using the risk reduction parameters instead of the WTP. We tested the sensitivity to the scope using a t-test. We only compare against the risk reductions offered in the same alternative (see Figure 1). For instance, we did not test differences between Traffic risk (30/200) and Traffic risk (35/200) because the respondent could face both risks in the same choice situation, which flaws the scope test logic. Then, the t-test results of the internal scope test are summarized in Table A4. Our estimates always passed the weak internal scope test, but not the strong internal scope test.

Table A3. MNL estimations to test risk proportionality.

Attributes (reductions/mortality)	**MNL8** **Coefficient (Rob t-ratio)**	**Attributes (reductions/mortality)**	**MNL9** **Coefficient (Rob t-ratio)**
Traffic risk (5/200)	-0.3623 (-1.06)	Traffic risk (10/210)	Baseline alt. C
Traffic risk (10/200)	Baseline alt. B and C	Traffic risk (15/210)	Baseline alt. B
Traffic risk (15/200)	-0.2577 (1.39)	Traffic risk (20/210)	0.3115 (2.57)
Traffic risk (25/200)	0.6917 (-0.74)	Traffic risk (25/210)	0.2076 (1.70)
Traffic risk (30/200)	0.4234 (2.03)	Traffic risk (30/210)	0.6364 (5.58)
Traffic risk (35/200)	0.5926 (2.41)	Traffic risk (35/210)	0.4170 (3.51)
Cardiorespiratory risk (5/200)	Baseline alt. B	Cardiorespiratory risk (5/350)	Baseline alt. B
Cardiorespiratory risk (10/200)	Baseline alt. C	Cardiorespiratory risk (15/350)	Baseline alt. C
Cardiorespiratory risk (15/200)	0.2792 (0.53)	Cardiorespiratory risk (25/350)	0.3321 (1.98)
Cardiorespiratory risk (20/200)	0.3774 (2.40)	Cardiorespiratory risk (35/350)	0.1702 (1.31)
Cardiorespiratory risk (25/200)	0.2326 (0.80)	Cardiorespiratory risk (45/350)	0.4943 (4.07)
Cardiorespiratory risk (30/200)	0.9783 (3.61)	Cardiorespiratory risk (55/350)	0.3128 (2.68)
Future cardiorespiratory risk (200/5400)	Baseline alt. B	Future cardiorespiratory risk (300/3900)	Baseline alt. B
Future cardiorespiratory risk (300/5400)	Baseline alt. C	Future cardiorespiratory risk (360/3900)	Baseline alt. C
Future cardiorespiratory risk (400/5400)	0.0639 (0.30)	Future cardiorespiratory risk (420/3900)	0.2112 (1.64)
Future cardiorespiratory risk (500/5400)	0.5325 (4.71)	Future cardiorespiratory risk (480/3900)	0.2135 (1.82)

Future cardiorespiratory risk (600/5400)	0.0287 (0.08)	Future cardiorespiratory risk (540/3900)	0.2605 (1.65)
Future cardiorespiratory risk (700/5400)	0.5125 (2.62)	Future cardiorespiratory risk (600/3900)	0.4462 (4.14)
Future cardiorespiratory risk (900/5400)	0.1770 (0.71)	Cost	-0.00002 (-0.60)
Cost	0.00003 (0.35)	-	-
Log-likelihood choice model	-3483	Log-likelihood choice model	-2486
N	378	N	265

Source: Author’s elaboration. Numbers in parentheses represent the relationship between risk reduction and baseline risk for the specific age group. We always chose the lower risk reduction as the reference group for allowing the parameter identification. However, in MNL8, we only used Traffic risk (10/200) as the reference group because that level was presented in alternatives B and C.

Table A4. Scope tests

<table>
<tr><th colspan="4">Internal scope test</th></tr>
<tr><th colspan="2">25-44 years old group</th><th colspan="2">45-64 years old group</th></tr>
<tr><th>Alternative hypothesis</th><th>P-value (t statistic) weak test / strong test</th><th>Alternative hypothesis</th><th>P-value (t statistic) weak test / strong test</th></tr>
<tr><td>Traffic risk (35/200) > | ≠ Traffic risk (30/200)</td><td>0.000 (30.6) / 0.000 (16.6)</td><td>Traffic risk (30/210) > | ≠ Traffic risk (20/210)</td><td>0.000 (95.3) / 0.000 (38.5)</td></tr>
<tr><td>Cardiorespiratory risk (30/200) > | ≠ Cardiorespiratory risk (20/200)</td><td>0.000 (111.9) / 0.000 (66.9)</td><td>Traffic risk (35/210) > | ≠ Traffic risk (25/210)</td><td>0.000 (60.1) / 0.000 (55.1)</td></tr>
<tr><td>Future cardiorespiratory risk (700/5400) > | ≠ Future cardiorespiratory risk (500/5400)</td><td>0.000 (5.2) / 0.000 (54.0)</td><td>Cardiorespiratory risk (45/350) > | ≠ Cardiorespiratory risk (25/350)</td><td>0.000 (38.3) / 0.000 (31.2)</td></tr>
<tr><td></td><td></td><td>Future cardiorespiratory risk (600/3900) > | ≠ Future cardiorespiratory risk (480/3900)</td><td>0.000 (71.3) / 0.000 (48.1)</td></tr>
</table>

Source: Author’s elaboration.

APPENDIX B

Table B1. Measurement model estimated thresholds parameters.

Traffic Controllability	Coefficient (Robust t-ratio)	Traffic Concern	Coefficient (Robust t-ratio)	Cardiorespiratory Controllability	Coefficient (Robust t-ratio)	Cardiorrespiratory Concern	Coefficient (Robust t-ratio)
τ_{11_1}	-0.81 (-1.91)	τ_{12_1}	-4.23 (-8.95)	τ_{13_1}	-1.69 (-6.24)	τ_{14_1}	-1.41 (-14.6)
τ_{11_2}	0.56 (1.36)	τ_{12_2}	-2.9 (-6.93)	τ_{13_2}	-0.73 (-2.83)	τ_{14_2}	-0.73 (-8.66)
τ_{11_3}	2.26 (5.5)	τ_{12_3}	-1.31 (-3.52)	τ_{13_3}	0.48 (-2.83)	τ_{14_3}	0.20 (2.35)
τ_{11_4}	3.59 (8.46)	τ_{12_4}	0.30 (0.84)	τ_{13_4}	1.80 (7.01)	τ_{14_4}	1.17 (11.74)
τ_{21_1}	-0.68 (-1.31)	τ_{22_1}	-4.72 (-9.49)	τ_{23_1}	-1.54 (-3.97)	τ_{24_1}	-3.28 (-17.12)
τ_{21_2}	0.76 (1.53)	τ_{22_2}	-3.57 (-8.00)	τ_{23_2}	-0.07 (-0.18)	τ_{24_2}	-2.65 (-17.85)
τ_{21_3}	2.66 (5.38)	τ_{22_3}	-1.99 (-5.05)	τ_{23_3}	1.44 (3.82)	τ_{24_3}	-1.32 (-13.18)
τ_{21_4}	4.49 (8.63)	τ_{22_4}	-0.25 (-0.68)	τ_{23_4}	3.26 (8.38)	τ_{24_4}	-0.02 (-0.17)
τ_{31_1}	-0.86 (-1.62)	τ_{32_1}	-4.61 (-10.25)	τ_{33_1}	-2.93 (-7.16)	τ_{34_1}	-2.07 (-17.00)
τ_{31_2}	0.55 (1.06)	τ_{32_2}	-3.28 (-8.14)	τ_{33_2}	-1.36 (-3.53)	τ_{34_2}	-1.55 (-15.24)
τ_{31_3}	2.58 (4.84)	τ_{32_3}	-1.79 (-4.82)	τ_{33_3}	0.40 (1.10)	τ_{34_3}	-0.42 (-4.92)
τ_{31_4}	4.23 (7.41)	τ_{32_4}	0.07 (0.20)	τ_{33_4}	2.12 (5.43)	τ_{34_4}	0.83 (8.37)
τ_{41_1}	-0.42 (-0.51)	τ_{42_1}	-5.81 (-12.12)	τ_{43_1}	-2.11 (-5.05)	τ_{44_1}	-3.07 (-17.13)
τ_{41_2}	1.88 (2.11)	τ_{42_2}	-4.65 (-11.33)	τ_{43_2}	-0.47 (-1.16)	τ_{44_2}	-2.53 (-17.57)
τ_{41_3}	3.98 (4.08)	τ_{42_3}	-3.25 (-9.12)	τ_{43_3}	0.97 (2.28)	τ_{44_3}	-1.45 (-14.27)
τ_{41_4}	6.14 (5.76)	τ_{42_4}	-1.26 (-3.75)	τ_{43_4}	2.55 (5.64)	τ_{44_4}	0.01 (0.14)
τ_{51_1}	0.10 (0.10)	τ_{52_1}	-5.07 (-10.88)	τ_{53_1}	-1.98 (-9.52)	τ_{54_1}	-3.27 (-16.54)
τ_{51_2}	2.53 (2.33)	τ_{52_2}	-4.21 (-9.95)	τ_{53_2}	-1.00 (-5.11)	τ_{54_2}	-2.53 (-17.79)
τ_{51_3}	4.99 (4.02)	τ_{52_3}	-2.87 (-7.85)	τ_{53_3}	-0.28 (-1.41)	τ_{54_3}	-1.75 (-15.99)
τ_{51_4}	7.18 (5.08)	τ_{52_4}	-1.11 (-3.52)	τ_{53_4}	0.64 (3.16)	τ_{54_4}	-0.71 (-7.51)
τ_{61_1}	0.28 (0.3)	τ_{62_1}	-5.41 (-10.83)				
τ_{61_2}	2.39 (2.4)	τ_{62_2}	-4.57 (-10.02)				
τ_{61_3}	4.43 (3.92)	τ_{62_3}	-3.18 (-8.35)				
τ_{61_4}	6.37 (5.02)	τ_{62_4}	-1.39 (-4.3)				

Source: Author's elaboration.

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Figure 1. Choice experiment alternatives and levels by age group

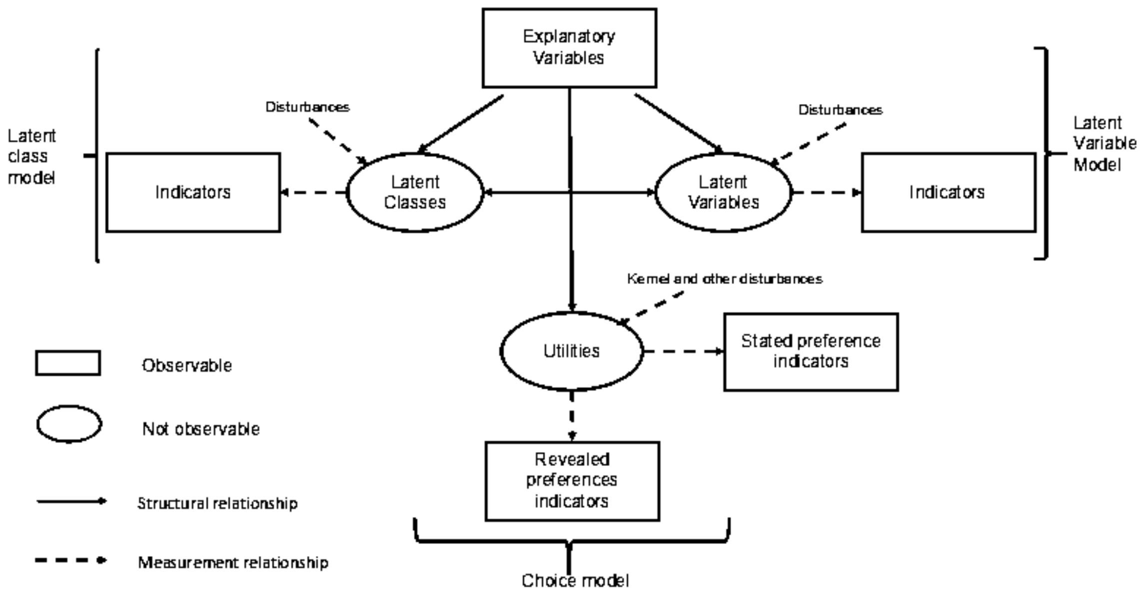
	Levels		
Attributes	Age group 25-44	Age group 45-64	Age group 65+
Traffic accidents deaths			
Base risk deaths/year:	200 in 1,900,000	210 in 1,500,000	100 in 600,000
Reductions alternative B deaths/year:	10, 25, 30, 35	15, 25, 35	5, 15, 25
Reductions alternative C deaths/year:	5, 10, 15, 30	10, 20, 30	0, 10, 20
Cardiorespiratory diseases associated with air pollution			
Base risk deaths/year:	200 in 1,900,000	350 in 1,500,000	1,880 in 600,000
Reductions alternative B deaths/year:	5, 15, 25	5, 25, 45	50, 150, 250
Reductions alternative C deaths/year:	10, 20, 30	15, 35, 55	100, 200, 300
Future cardiorespiratory diseases associated with air pollution			
Base risk deaths/year:	5,400 in 1,900,000	3,900 in 1,500,000	0 in 600,000
Reductions alternative B deaths/year:	200, 400, 600	300, 420, 540	0
Reductions alternative C deaths/year:	300, 500, 700, 900	360, 480, 600	0
Monthly cost in Chilean pesos			
Alternative B:	$1,100, $2,300, $3,500		
Alternative C:	$500, $1,700, $2,900		

Figure 2. Example of choice set for the 45-64 age group

Choice sets	Age group 45-64 years old		
The risk that YOU face of dying from…	Status Quo (Alternative A)	Alternative B	Alternative C
Traffic accidents People in your age group who might die each year from traffic accidents, until you turn 65 years old	210	185	190
Cardiorespiratory diseases associated with air pollution People in your age group who might die each year from cardiorespiratory diseases associated with air pollution, until you turn 65 years old	350	345	295
Future cardiorespiratory diseases associated with air pollution People more than 65 years old who might die each year, after you turned 65 years old, from cardiorespiratory diseases associated with air pollution.	3900	3480	3420
Monthly cost in Chilean pesos (permanent)	$0	$2300 (US$ 3.83)	$1700 (US$ 2.83)

Source: Modified from GreenLabUC (2014).

Figure 3. Generalized random utility framework



Source: Modified from Ben-Akiva, McFadden, et al. (2002)

Table 1. Descriptive statistics Likert scale questions used for HCM.

	Statement	Mean value
	Traffic risk	
	To what degree do you think you can control the occurrence of severe traffic accidents?	
L_1	If you ride your bicycle during highly congested hours.	3.04
L_2	If you circulate on high-speed highways.	3.03
L_3	If you circulate during night hours.	3.10
L_4	If you drive at a higher speed than allowed.	3.00
L_5	If you pass a crosswalk with the yellow traffic light.	2.91
L_6	If you overtake another vehicle where not allowed.	2.92
	How concerned are you about having a traffic accident with severe consequences?	
L_7	If you ride your bicycle during highly congested hours.	3.61
L_8	If you circulate on high-speed highways.	3.85
L_9	If you circulate during night hours.	3.77
L_{10}	If you drive at a higher speed than allowed.	4.28
L_{11}	If you pass a crosswalk with the yellow traffic light.	4.27
L_{12}	If you overtake another vehicle where not allowed.	4.38
	Cardiorespiratory risks	
	To what degree do you think you can control the exposure to air pollution that can cause health problems with severe consequences?	
L_{13}	If you walk outdoors regularly	2.90
L_{14}	If you live in an area with poor air quality.	2.49
L_{15}	If you regularly perform activities that involve physical effort.	3.07
L_{16}	If you move during winter to an area with environmental pollution.	2.75
L_{17}	If you live in poorly ventilated spaces and are exposed to tobacco smoke.	3.36
	How concerned are you about suffering health problems such as cardiorespiratory diseases with severe consequences as a result of air pollution?	
L_{18}	If you walk outdoors regularly	3.28
L_{19}	If you live in an area with poor air quality.	4.27
L_{20}	If you regularly perform activities that involve physical effort.	3.73
L_{21}	If you move during winter to an area with environmental pollution.	4.26
L_{22}	If you live in poorly ventilated spaces and are exposed to tobacco smoke.	4.46

Source: Author's elaboration based on the GreenLabUC (2014) survey. The Likert scale was from 1= not worry (concern) to 5= very worry (concern).

Table 2. Factor analysis.

Likert scale question	Factor 1	Factor 2	Factor 3	Factor 4
L_1. If you live in poorly ventilated spaces and are exposed to tobacco smoke. (Control).			0.550	
L_2. If you circulate on high-speed highways. (Control).	0.762			
L_3. If you circulate during night hours. (Control).	0.772			
L_4. If you drive at a higher speed than allowed. (Control).	0.888			
L_5. If you pass a crosswalk with a yellow traffic light. (Control).	0.915			
L_6. If you overtake another vehicle where not allowed. (Control).	0.908			
L_7. If you ride your bicycle during highly congested hours. (Concern).		0.708		
L_8. If you circulate on high-speed highways (Concern).		0.745		
L_9. If you circulate during night hours. (Concern).		0.758		
L_{10}. If you drive at a higher speed than allowed. (Concern).		0.705		
L_{11}. If you pass a crosswalk with a yellow traffic light. (Concern).		0.673		
L_{12}. If you overtake another vehicle where not allowed. (Concern).		0.633		
L_{13}. If you walk outdoors regularly. (Control).			0.597	
L_{14}. If you live in an area with poor air quality. (Control).			0.765	
L_{15}. If you regularly perform activities that involve physical effort. (Control).			0.761	
L_{16}. If you move during winter to an area with environmental pollution. (Control).			0.809	
L_{17}. If you live in poorly ventilated spaces and are exposed to tobacco smoke. (Control).			0.550	
L_{18}. If you walk outdoors regularly. (Concern).				0.547
L_{19}. If you live in an area with poor air quality. (Concern).				0.794
L_{20}. If you regularly perform activities that involve physical effort. (Concern).				0.598
L_{21}. If you move during winter to an area with environmental pollution. (Concern).				0.746
L_{22}. If you live in poorly ventilated spaces and are exposed to tobacco smoke. (Concern).				0.584

Source: Author's elaboration based on survey GreenLabUC (2014). In parentheses, we report whether the Likert scale question is about control or concerns the risks.

Table 3. Descriptive statistics of relevant variables.

Variables	Used sample		Full sample	
	Mean	Standard deviation	Mean	Standard deviation
Traffic accident (1 = yes)	0.16	0.37	0.16	0.36
Cardiorespiratory disease (1 = yes)	0.28	0.45	0.28	0.45
Gender (1= male)	0.43	0.50	0.39	0.49
Education 2 (1 = belong to this group)	0.37	0.48	0.37	0.46
Education 3 (1 = belong to this group)	0.42	0.49	0.37	0.48

Source: Author’s elaboration based on the GreenLabUC (2014) survey. N = 758.

Table 4. Structural and measurement model results

	Traffic controllability	**Traffic concern**	**Cardiorespiratory controllability**	**Cardiorespiratory concern**
Explanatory variables	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)
Traffic accident	0.47 (4.53)	0.02 (0.14)	-	-
Cardiorespiratory disease	-	-	-0.19 (-1.35)	-0.26 (14.02)
Gender	0.39 (3.51)	-0.25 (-1.78)	0.19 (1.73)	-0.51 (-34.21)
Education 2	0.53 (2.68)	-0.10 (-0.65)	-0.14 (-0.84)	0.43 (14.21)
Education 3	0.40 (1.96)	-0.30 (-1.80)	-0.35 (-2.39)	0.75 (40.72)

Traffic controllability		**Traffic concern**		**Cardiorespiratory controllability**		**Cardiorespiratory concern**	
Coefficient (Robust t-ratio)		Coefficient (Robust t-ratio)		Coefficient (Robust t-ratio)		Coefficient (Robust t-ratio)	
γ_1	2.42 (10.36)	γ_7	2.41 (9.4)	γ_{13}	1.84 (9.48)	γ_{18}	0.48 (4.14)
γ_2	3.05 (9.65)	γ_8	2.51 (9.01)	γ_{14}	2.79 (11.19)	γ_{19}	0.82 (5.25)
γ_3	3.04 (10.96)	γ_9	2.46 (10.99)	γ_{15}	2.77 (10.16)	γ_{20}	0.68 (5.27)
γ_4	4.84 (11.82)	γ_{10}	2.44 (7.98)	γ_{16}	3.12 (11.07)	γ_{21}	0.80 (5.53)
γ_5	5.67 (8.59)	γ_{11}	2.09 (7.8)	γ_{17}	1.40 (9.4)	γ_{22}	0.89 (5.87)
γ_6	5.18 (9.21)	γ_{12}	2.08 (7.78)		-		-

Source: Author’s elaboration

Table 5. Estimation results.

Explanatory variables	MNL1 Coefficient (Robust t-ratio)	MNL 2 Coefficient (Robust t-ratio)	HCM Coefficient (Robust t-ratio)
ASC	-0.2217 (-1.70)	0.1172 (0.53)	-2.5501 (-5.97)
Traffic risk	-0.0177 (-8.14)	-0.0154 (-7.54)	-0.0155 (-7.83)
Current cardiorespiratory risk	-0.00001 (-0.02)	-0.0012 (-1.89)	-0.0019 (-2.85)
Future Cardiorespiratory risk	-0.0006 (-4.07)	-0.0003 (-2.42)	-0.0002 (-2.22)
Cost	-0.0001 (-6.46)	-0.0001 (-6.62)	-0.0001 (-6.60)
Traffic Controllability	-	-0.0007 (-0.77)	0.0059 (5.89)
Traffic Concern	-	-0.0032 (-3.26)	0.0097 (7.99)
Cardiorespiratory Controllability	-	-0.0001 (-0.66)	0.0014 (4.32)
Cardiorespiratory Concern	-	0.0003 (1.88)	-0.0314 (-10.96)
Traffic WTP (in US$)	0.2572 (0.1665;0.3479)	0.2680 (0.1859;0.3501)	0.2079 (0.1272;0.2885)
Current cardiorespiratory WTP (in US$)	-	-	0.1132 (0.0780;0.1485)
Future cardiorespiratory WTP (in US$)	0.0084 (0.0042;0.0126)	0.0043 (0.0006;0.0080)	-
Log-likelihood choice model	-7139	-7084	-5059
Log-likelihood hybrid model	-	-	-25253
N	758	758	758

Source: Author’s elaboration. WTP values in parentheses are their 95% confidence intervals. WTP standard errors were calculated using the delta method.

Table 6. VSL calculated for MNL and HCM in US$ million.

	MNL1	MNL2	HCM
Traffic VSL average	4.65 (4.68)	4.69 (4.72)	3.76 (3.78)
Traffic VSL LB	3.01 (3.03)	3.22 (3.24)	2.30 (2.31)
Traffic VSL UB	6.27 (6.33)	6.16 (6.20)	5.22 (5.25)
Current cardiorespiratory VSL average	-	-	2.05 (2.06)
Current cardiorespiratory VSL LB	-	-	1.41 (1.42)
Current cardiorespiratory VSL UB	-	-	2.68 (2.70)
Future cardiorespiratory VSL average	0.15 (0.15)	0.08 (0.08)	-
Future cardiorespiratory VSL LB	0.08 (0.08)	0.01 (0.01)	-
Future cardiorespiratory VSL UB	0.23 (0.23)	0.15 (0.15)	-

Source: Author's elaboration. All values are in US$ million. LB = Lower Bound, UB = Upper bound. In parentheses, we presented values adjusted by inflation and real income growth to 2019 US$.