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

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Manuel Barrientos, Felipe Vásquez Lavín, and Roberto D. Ponce Oliva*

Abstract

We explore the incorporation of latent variables (attitudes, beliefs, and perceptions) in the estimation of the value of a statistical life using a hybrid choice model framework. Latent variables cannot be observed; therefore, one must indirectly infer information about them through questionnaires. We used two latent variables: risk controllability and concerns regarding traffic and cardiorespiratory risks. The use of a hybrid choice model allows us to explicitly model unobserved taste heterogeneity, to improve the behavioral realism of the model, to enhance the model efficiency (due to the incorporation of more information about the latent variables and an increase in the accuracy of predictions), and to help design effective policies related to risk reduction. For traffic risks, we estimate a value of a statistical life of US$ 4.58 million using the conditional logit model and US$ 4.73 million using the hybrid choice model. Our results provide new evidence on the interaction between self-perceived control and risks, stressing the inverse relationship between control and willingness to pay for risk reduction, and the positive relationship between risk concerns and willingness to pay.

Keywords: value of a statistical life; latent variables; hybrid choice models; willingness to pay; reduction in air quality risk; reduction in traffic risk

JEL Codes: D91, R41, Q51

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1. Introduction

In this article, we explore the incorporation of latent variables (LVs), 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 defined as the willingness to pay (WTP) for or willingness to accept (WTA) reductions or increases in the risk of premature death (Viscusi, Huber et al. 2014).

For many years, the economic literature has recognized the role of LVs in the estimation of VSL, but few applications attempt to include them in VSL estimation (Carlsson, Daruvala et al. 2010, Alberini and Ščasný 2011). LVs cannot be observed; therefore, one must indirectly infer information about them through questionnaires. Examples of LVs are risk controllability, fear, anxiety, voluntariness, and concern about hazards. In recent decades, choice modelers have sought to incorporate these types of attitudes and perceptions into their models to improve behavioral realism (Abou-Zeid and 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 VSL (Jones-Lee 1985). Another classical example is the analysis of cancer as a "dreaded disease" (Viscusi, Huber et al. 2014), which has shown a higher VSL than less dreaded diseases (Savage 1993, Revesz 1999, Hammitt and Liu 2004, Alberini and Scasny 2010, Hammitt and Haninger 2010, Tonin, Alberini et al. 2012, Alberini and Ščasný 2013, Olofsson, Gerdtham et al. 2019). Other examples of attitudes included in choice models are aversion to financial risks (Eeckhoudt and Hammitt 2004, Hammitt and Haninger 2010, Parada-Contzen 2019) or risky behaviors (Parada-Contzen 2019).

Previous attempts to include LVs in the estimation of VSL have incorporated them directly as explanatory variables in regression models (Chilton, Jones-Lee et al. 2006, Carlsson, Daruvala et al. 2010, Alberini and Ščasný 2013, Olofsson, Gerdtham et al. 2019). However, McFadden (1986), Ashok, Dillon et al. (2002), Morikawa, Ben-Akiva et al. (2002) and Hess and Beharry-Borg (2012) note that the direct incorporation of LVs into the definitions of the regression analysis may generate multicollinearity, little predictive validity, and measurement error. Recently, Daziano and Rizzi (2015) and González, Román et al. (2018) identify the need to include LVs in the estimation of VSL using the HCM approach. In this paper, we contribute to this objective by exploring the implications of including LVs in the estimation of VSL using HCM.

The use of HCM provides the capacity to explicitly model unobserved taste heterogeneity, improve the behavioral realism of the model, enhance the model efficiency due to the incorporation of more information about LVs and increased accuracy of predictions, and help design more effective policies related to risk reduction (Abou-Zeid and Ben-Akiva 2014, Vij and Walker 2014). For instance, Bolduc, Boucher et al. (2008) incorporate *environmental concerns* as an LV in the choice of new technologies in vehicles, whereas Mariel, Meyerhoff et al. (2015) use an HCM to investigate public sensitivity to the externalities associated with wind turbines using the LV *pro-wind power generation*. Following this latter methodology, Bello and Abdulai (2018) estimate the WTP for environmental and health gains from organic products using the LV *environmental* and *health concerns*. Hess and Beharry-Borg (2012) study the WTP for water quality improvements of beach visitors in Tobago, including *pro-intervention attitude* as an LV in the model. For a more comprehensive review of the use of HCM, refer to Kim, Rasouli et al. (2014) and Bouscasse (2018)[1].

The social valuation of risk reduction (VSL) has a long history in economics. It has been a relevant component in shaping public policies, including those related to health, traffic security, and the environment (Viscusi and Aldy 2003, Ashenfelter 2006). It depends on the characteristics of the population, such as income, the reference level of risk, and cultural and demographic variables (Chilton, Covey et al. 2002, Alberini, Cropper et al. 2004, Smith, Evans et al. 2004, Aldy and Viscusi 2007, Aldy and Viscusi 2008, Alberini and Ščasný 2011). VSL also depends on the attributes of the risk under analysis (cause of death, latency, size of the risk change) (Hammitt and Liu 2004) and people's perceptions and attitudes (Carlsson, Johansson-Stenman et al. 2004, Carlsson, Daruvala et al. 2010, Andersson and Treich 2011). Other issues that affect the estimates are sample errors, publication bias, and other methodological decisions (Viscusi and Masterman 2017, Viscusi 2018). Therefore, it is not surprising to find differences in VSL estimations between countries or even between cities in the same country (Miller 2000, Viscusi and Aldy 2003, Dekker, Brouwer et al. 2011, Zan and Scharff 2017).

VSL can be estimated using either the revealed preference (RP) approach, generally through the hedonic wage model (HWM) (Kniesner, Viscusi et al. 2012), or the stated preference (SP) approach, including contingent valuation (CV) and choice experiments (CEs) (Krupnick, Alberini et al. 2002, de Blaeij, Florax et al. 2003, Alberini 2019, Bleichrodt, Courbage et al. 2019). In recent decades, CEs have become a common approach to estimate VSL in SP (Hensher, Rose et al. 2005). 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 (Hanley, Wright et al. 1998). We are aware of some critics regarding the use of CEs in the valuation of mortality risk reductions (Andersson, Hole et al. 2016); nevertheless, our focus is on exploring the incorporation of LVs in the estimation of the VSL in the context of SP.

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

We contribute to the literature in three ways. First, to the best of our knowledge, we are the first study that incorporates LVs to explicitly estimate VSL using the HCM framework. In our application, we use two LVs: risk controllability and concerns regarding traffic and cardiorespiratory risks. We are interested in these variables because the literature has highlighted their influence on WTP (Jones-Lee and Loomes 1995, Haddak, Lefèvre et al. 2016). Regarding controllability, there is evidence that some individuals believe they control risk more efficiently than other individuals, which is known as the superiority illusion bias (Klein and Kunda 1994). Regarding concerns, although individuals periodically see or read about accidents, some people perceive them as external, and they are not concerned about risks with a very low probability of occurrence. On the other hand, some people with excessive concern about hazards could suffer effects on their lifetime productivity (Slovic, Fischhoff et al. 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 distinguishes between different kinds of risks.

The remainder of this article is organized as follows: First, we present the methodology of the HCM and VSL. Then, we describe our data and the specification of the HCM. In the fourth section, we provide the main results of our estimation, a discussion of our results, and a comparison with other VSL estimations in the literature. Finally, we present our conclusions.

2. Methodology

Over the last 20 years, the HCM has become the standard framework for including LVs in choice models. The HCM is based on a strand of behavioral theory (Bouscasse 2018), most commonly the theory of planned behavior (Ajzen 1991). This theory contends that the *intention* to perform a behavior is a central factor in explaining behavior. Furthermore, the *attitude toward the behavior*, the *subjective norm*, and the *perceived behavioral control* affect the intention toward the behavior[2].

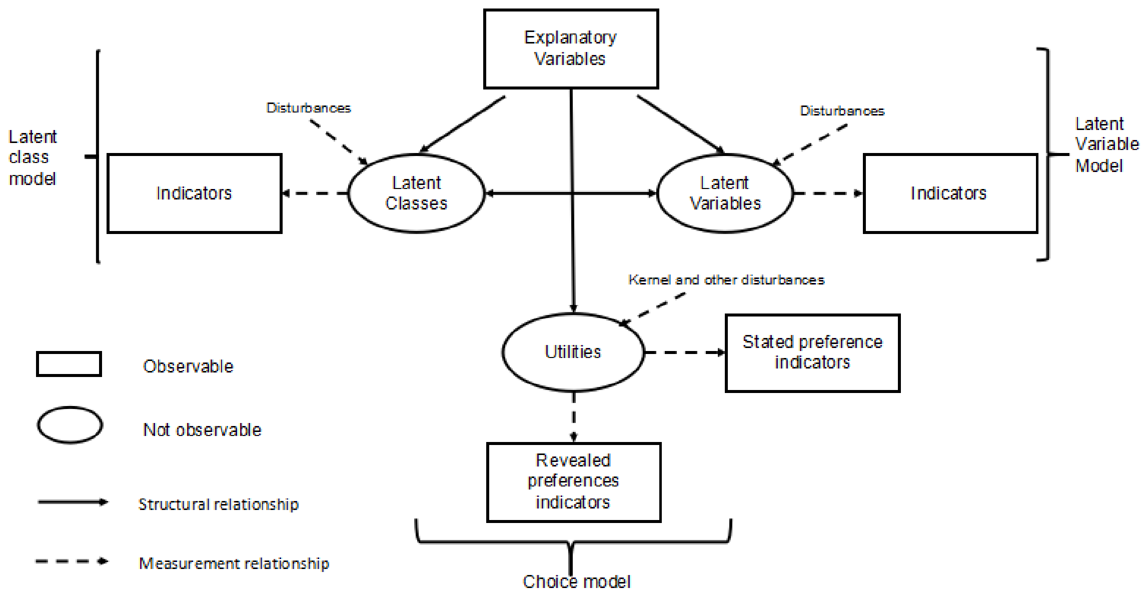
HCM is an extension of the classical choice models, including the conditional logit, the nested logit, the mixed logit, or the multinomial probit.[3] Figure *1*, suggested by Walker and Ben-Akiva (2002), depicts the main elements of the choice modeling framework. In the center, we observe the (latent) utility level perceived by an individual associated with her/his choice. This utility depends on the observable explanatory variables, including individuals´ characteristics and

[2] See Ajzen (1985) and Ajzen (1991) for details on the theory of planned behavior.

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

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. The left side of the figure represents one of the approaches to capture heterogeneity across individuals; the latent class model that divides the sample into different random classes representing different responses to the attributes of the alternatives.

Figure 1. Generalized Random Utility Framework



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

For our purposes, the right side is more relevant. It shows the LVs (also in a circle reflecting that they are unobserved variables) that represent attitudes, beliefs, or perceptions. These variables also depend on a set of individual attributes and disturbances. Since these variables cannot be observed, researchers use indirect approaches to measure these variables, called *indicators*.

Several authors have addressed issues affecting the estimation of hybrid choice models (Ashok, Dillon et al. 2002, Bolduc and Alvarez-Daziano 2010, Raveau, Álvarez-Daziano et al. 2010). There are two approaches to estimating an HCM: a sequential two-step approach and a simultaneous estimation. In the first step of the sequential approach, one estimates an LV model, the coefficients and distribution of which will be used in the second stage. In the second stage, one estimates a choice model using the predicted LVs as explanatory variables. In contrast, in the simultaneous estimation, the choice and LV models are estimated jointly (Abou-Zeid and Ben-Akiva 2014).

The most commonly used model assumes a linearly additive functional form for the utility function attained by an individual by choosing alternative *i* in choice situation *t* given by[4]:

$$U_{it} = \beta' X_{it} + \alpha_r' z_{ir}^* + \varepsilon_{it} \tag{1}$$

$$z_r^* = \theta_{kr}' s_k + \mu_r$$

where X_{it} is a matrix of observed explanatory variables (individuals' attributes and alternatives' attributes), and z_{ir}^* is a vector of the r latent variables, also known as a *structural model*. β is a vector of unknown parameters, and ε_{it} is a vector of disturbances. The LVs (z_{ir}^*) are explained by a vector s_k of k explanatory variables; these are usually sociodemographic variables at an individual level but can also be any other type of variable (Kamargianni, Ben-Akiva et al. 2014). Finally, μ_r is a disturbance with a normal distribution 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 et al. (2012), Daly, Hess et al. (2012), and Vij and Walker (2014), among others.

Neither the structural model nor the indirect utility is identifiable, because we do not observe z_r^* or U_{it}. For these reasons, it is necessary to consider *measurement models* for them (Bahamonde-Birke and Ortuzar 2015). In the case of the utility level, we used the classical binary measurement.

$$y_{it} = \begin{cases} 1 & if \quad U_{it} > U_{jt} \quad \forall\ i \neq j \\ 0 & Otherwise \end{cases} \tag{2}$$

For the LV, we use:

$$I_p = \varphi_p + \gamma_p z^* + \zeta_p \qquad \zeta_p \sim N(0, \Theta_p) \tag{3}$$

In this expression, $y_{it} = 1$ denotes the choice of alternative *i* by an individual in choice situation *t*, and the subscripts i and *j* represent the j=1,…,J alternatives. Equation (3) represents the measurement model for the LV, where I_p is a vector of p indicators of the LV for each individual[5], φ_p is a constant for each (p) indicator, γ_p is a vector of unknown parameters that associate the LV with the indicators, and ζ_p is a vector of disturbance terms that are normally distributed with mean

[4] For simplicity, the subscript for individuals is omitted.
[5] These indicators can take many forms. Márquez, Cantillo et al. (2020) describe and evaluate a group of them that have been used in HCMs.

zero and standard deviation Θ_p. In many cases, the mean of each Likert question is subtracted from the original value to reduce the number of estimated parameters; in other words, φ_p is not estimated because the indicators are centered on zero.

Assuming that ε_{it} is independent and identically distributed extreme value type I, and considering the repeated choice nature of a CE (Revelt and Train 1998), the probability of choosing alternative *i* is given by:

$$\mathrm{P}(\mathrm{y_{it}}|\mathrm{z}^*, \mathrm{x}, \beta, \alpha) = \Pr(y_{it} = 1) = \prod_{t=1}^{T} \frac{\exp\,(\beta' X_{it} + \alpha_r' z_{ir}^*)}{\sum_J \exp\,(\beta' X_{jt} + \alpha_r' z_{jr}^*)} \tag{4}$$

The structural model is estimated following a multiple indicator multiple causes (MIMIC) model, wherein the LV is explained by exogenous causes (Jöreskog and Goldberger 1975). The measurement model may have different specifications. Three possible formulations for the indicators are continuous, binary, and ordered (Bolduc and Alvarez-Daziano 2010, Daly, Hess et al. 2012). We use the continuous definition because it requires significantly less computational time and is widely used in the literature. Therefore, the joint density function of I_p conditional on the vector of parameters γ_p, disturbance terms ζ_p and realizations of LV z^* is:

$$\mathbf{f}\left(\mathbf{I_p} \middle|\, \boldsymbol{\gamma_p}, \mathbf{z}^*, \boldsymbol{\zeta_p}\right) = \prod_{\mathbf{p=1}}^{\mathbf{P}} \mathbf{f}\left(\mathbf{I_p} \middle| \boldsymbol{\gamma_p}, \mathbf{z}^*, \boldsymbol{\zeta_p}\right) = \prod_{\mathbf{p=1}}^{\mathbf{P}} \frac{\mathbf{1}}{\boldsymbol{\zeta_p}\sqrt{\mathbf{2}\boldsymbol{\pi}}} \boldsymbol{e}^{-\frac{(\mathbf{I_p} - \boldsymbol{\gamma_p} \boldsymbol{z}^*)^2}{2\boldsymbol{\zeta_p}^2}} \tag{5}$$

where we have assumed independence among indicators. Therefore, the joint probability of the choice model with the LV indicators is obtained by multiplying the conditional probability of the choice by the function of the conditional density of the indicators and integrating over the density of LV z_r^*. That is:

$$\mathbf{P}(\mathbf{y_i}, \mathbf{I}|\mathbf{x_i}, \mathbf{s_k}, \boldsymbol{\lambda}) = \int_{\mathbf{z}^*} \mathbf{P}(\mathbf{y_i}|\mathbf{z}^*, \mathbf{x}, \boldsymbol{\beta}) \mathbf{f}\left(\mathbf{I_p} \middle|\, \boldsymbol{\gamma_p}, \mathbf{z}^*, \boldsymbol{\zeta_p}\right) \mathbf{g}(\mathbf{z}^*|\boldsymbol{\theta}, \boldsymbol{\alpha}) \mathbf{dz}^* \tag{6}$$

where $\lambda = \theta, \beta, \alpha, \gamma, \zeta$ are parameters to be estimated. The estimation of the probability of equation (6) requires calculating multiple integrals, so the literature provides different numeric methods and simulations[6]. To estimate our model, we use the R package Apollo (Hess and Palma 2019).

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

3. Data

We use data provided by the Chilean Ministry of the Environment collected by the project "Estimation of the value of statistical life associated with atmospheric pollution and traffic accidents," implemented by GreenLabUC (2014). The objective of this study was to estimate the WTP for reductions in air pollution and traffic risks in Chile using a CE. A survey was conducted in Santiago, Chile in 2014. The research team used four focus groups and three pilot surveys. The choice experiment 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 levels of the attributes vary along three age groups (25-44, 45-64, and over 65) because the perceived risks are different across them (Alberini, Cropper et al. 2004, Aldy and Viscusi 2008). An efficient design (Hensher, Rose et al. 2005) was used to obtain nine choice sets with three alternatives, including a status quo alternative (situation A) and two alternatives with reduced risks relative to the status quo (situation B and C). An example of a choice situation is presented in figure 2.

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

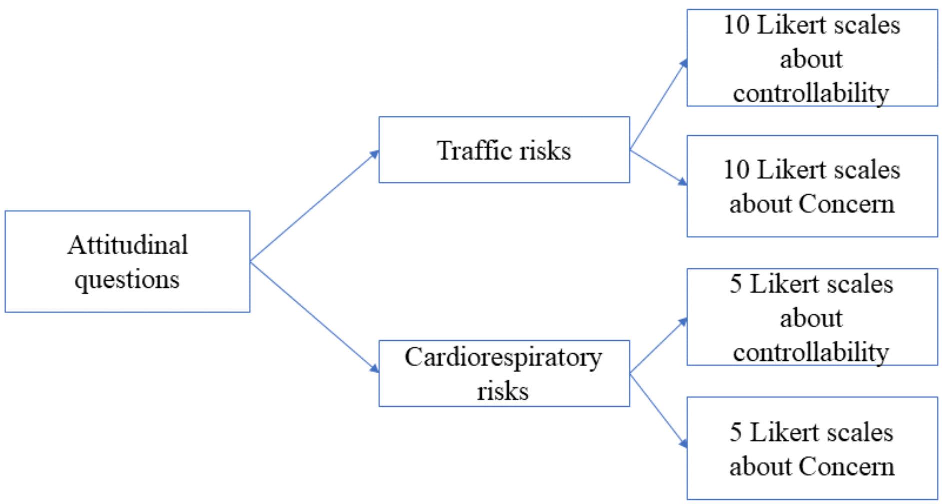
Choice sets	Age group 45-64 years old		
The risk that YOU face of dying from…	Status Quo (Situation A)	Situation B	Situation C
Traffic accidents People in your age group who might die each year from traffic accidents, until you turn 65 years old	210	185	190
Cardiorespiratory diseases associated with 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 turn 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).

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 1125 individuals.

A set of questions about the respondent's concern about risk and its controllability were included in the survey and divided into ten questions about traffic accidents (associated with the transport mode most used by the interviewee, which could be lightweight vehicle driver, public transport heavy vehicle driver, lightweight vehicle passenger, public transport user, bicycle or pedestrian) and five questions about 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. Figure 3 summarizes the Likert scales presented.

Figure 3. Likert Scale Questions Presented in the Survey



Source: Author's elaboration based on the GreenLabUC (2014) survey

We use exploratory factor analysis to discover the main attitudinal factors from the Likert scale questions. To explain the variance of the data, we use varimax rotation. With six main factors, we can explain 57% of the variance of the data; these factors are presented in table 1. We only used the first, second, fourth, and fifth factors that are related to motor vehicle transportation and excluded the third and sixth factors that are exclusively related to pedestrians. The first and second factors represent the perceived controllability of and concern about traffic risks, respectively. The fourth and fifth factors describe perceived controllability and concern about cardiorespiratory disease risks related to air pollution. We present the descriptive statistics of the chosen measurement items in table 2. Note that the items related to concern have a stronger positive preference than the items related to control.

We omitted 111 observations with no responses on the Likert scale questions. Moreover, 239 observations that correspond to pedestrians were also omitted. Hence, our final sample consisted of 775 individuals. The descriptive statistics of the relevant variables are presented in table 3, where the second column summarizes the statistics for the sample 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 socioeconomic characteristics of the sample.

Table 1. Exploratory Factor Analysis

Likert scale question	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
If you ride your bicycle during highly congested hours. (Concern).		**0.746**				
If you ride your bicycle during highly congested hours. (Control).	0.607					
If you circulate on high-speed highways (Concern).		**0.789**				
If you circulate on high-speed highways. (Control).	**0.712**					
If you circulate during night hours. (Concern).		**0.763**				
If you circulate during night hours. (Control).	**0.703**					
If you drive at a higher speed than allowed. (Concern).		**0.723**				
If you drive at a higher speed than allowed. (Control).	**0.878**					
If you pass a crosswalk with a yellow traffic light. (Concern).		0.619				
If you pass a crosswalk with a yellow traffic light. (Control).	**0.928**					
If you overtake another vehicle where not allowed. (Concern).		0.588				
If you overtake another vehicle where not allowed. (Control).	**0.918**					
If you hurry walking to your destination. (Concern).						
If you hurry walking to your destination. (Control).			0.576			
If you jaywalk. (Concern).						
If you jaywalk. (Control).			0.755			
If you walk using headphones listening to recordings or music. (Concern).						0.835
If you walk using headphones listening to recordings or music. (Control).			0.899			
If you walk using mobile telephones to communicate. (Concern).						0.811
If you walk using mobile telephones to communicate. (Control).			0.894			
If you walk outdoors regularly. (Concern).					0.584	
If you walk outdoors regularly. (Control).				0.513		
If you live in an area with poor air quality. (Concern).					**0.781**	
If you live in an area with poor air quality. (Control).				**0.702**		
If you regularly perform activities that involve physical effort. (Concern).					0.629	
If you regularly perform activities that involve physical effort. (Control).				**0.691**		
If you move during winter to an area with environmental pollution. (Concern).					**0.670**	
If you move during winter to an area with environmental pollution. (Control).				**0.804**		
If you live in poorly ventilated spaces and are exposed to tobacco smoke. (Concern).						
If you live in poorly ventilated spaces and are exposed to tobacco smoke. (Control).				0.628		

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

Table 2. 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?		
I_{11}	If you circulate on high-speed highways.	3.03
I_{21}	If you circulate during night hours.	3.10
I_{31}	If you drive at a higher speed than allowed.	3.01
I_{41}	If you pass a crosswalk with the yellow traffic light.	2.92
I_{51}	If you overtake another vehicle where not allowed.	2.93
How concerned are you about having a traffic accident with severe consequences?		
I_{12}	If you ride your bicycle during highly congested hours.	3.60
I_{22}	If you circulate on high-speed highways.	3.86
I_{32}	If you circulate during night hours.	3.78
I_{42}	If you drive at a higher speed than allowed.	4.28
Cardiorespiratory risks		
To what degree do you think you can control the exposure to air pollution that can cause health problems with severe consequences?		
I_{13}	If you live in an area with poor air quality.	2.49
I_{23}	If you regularly perform activities that involve physical effort.	3.08
I_{33}	If you move during winter to an area with environmental pollution.	2.76
How concerned are you about suffering health problems such as cardiorespiratory diseases with severe consequences as a result of air pollution?		
I_{14}	If you live in an area with poor air quality.	4.27
I_{24}	If you move during winter to an area with environmental pollution	4.27

Source: Author’s elaboration based on the GreenLabUC (2014) survey

Table 3. Descriptive Statistics of Relevant Variables

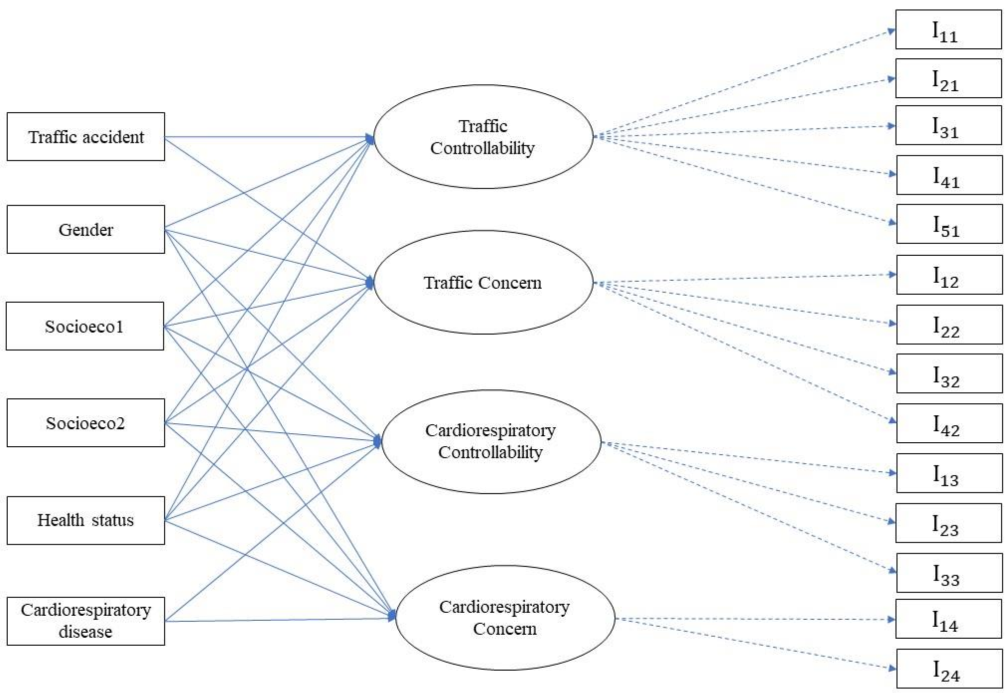
Variables	Used sample		Full sample	
	Mean	Standard deviation	Mean	Standard deviation
Gender (1= Male)	0.43	0.50	0.39	0.49
Traffic accident in the last three years (1 = yes)	0.16	0.36	0.16	0.36
Cardiorespiratory disease in the last three years (1 = yes)	0.28	0.45	0.28	0.45
Socioeconomic level 1 (1 = Belong to this group)	0.35	0.48	0.31	0.46
Socioeconomic level 2 (1 = Belong to this group)	0.32	0.47	0.31	0.46
Current health status (1 =very bad, 5 = very good)	3.67	0.81	3.69	0.85

Source: Author's elaboration based on the GreenLabUC (2014) survey. N = 775. Socioeconomic levels were derived based on educational level and the occupation of the head of the household.

4. Econometric Model Specification

Figure 4 presents the HCM setting with the structural and measurement relationships and their respective explanatory variables.

Figure 4. Hybrid Choice Model Setting



Source: Author's elaboration.

As the indicators were attribute-specific (Likert scale questions were separated by traffic and cardiorespiratory risks), we interact LVs with the attributes of traffic and current cardiorespiratory risks. To explore the effect of the incorporation of LVs in the estimation of VSL, we use the following specification:

$$\mathbf{U_0 = ASC_0 + \beta_1 * traff_0 + \alpha_1 * traff_0 * z_1^* + \alpha_2 * traff_0 * z_2^* + \beta_2 * cardio\_curr_0 +} \tag{7}$$
$$\mathbf{\alpha_3 * cardio\_curr_0 * z_3^* + \alpha_4 * cardio\_curr_0 * z_4^* + \beta_3 * cardio\_fut_0 + \delta_1 * cost_0 + \varepsilon_0}$$
$$\mathbf{U_1 = \beta_1 * traff_1 + \beta_2 * cardio\_curr_1 + \beta_3 * cardio\_fut_1 + \delta_1 * cost_1 + \varepsilon_1}$$
$$\mathbf{U_2 = \beta_1 * traff_2 + \beta_2 * cardio\_curr_2 + \beta_3 * cardio\_fut_2 + \delta_1 * cost_2 + \varepsilon_2}$$

where ASC_0 is the alternative-specific constant for the status quo situation. We also tested the utility specifications with and without alternative-specific constants for alternatives U_1 and U_2. The specification with an alternative-specific constant in the status quo had the best goodness of fit. $traff_i$ is the traffic risk reduction attribute in alternative i, $cardio\_curr_i$ is the current cardiorespiratory risk reduction, $cardio\_fut_i$ is the future cardiorespiratory risk reduction, and $\mathrm{cost_i}$ is the vector of prices associated with the different risk reductions offered in each alternative. The model includes the latent variable z_1^* denoting risk controllability regarding traffic accidents, z_2^* reflecting the concern about premature deaths in traffic accidents, and z_3^* and z_4^* representing the risks of controllability and concern about premature death due to a current cardiorespiratory disease.

The structural model (specified as a MIMIC model) contains sociodemographic variables that describe whether the individuals have had any traffic accident or cardiorespiratory disease in the last three years, a binary variable representing gender (1 for male), and two binary variables capturing the socioeconomic level of their households, where *socioeco1* denotes the lower segment, and *socioeco2* represents medium socioeconomic status. Additionally, we also consider a continuous variable for self-reported health status (ranging from 1 to 5, where 5 is very good health status). The random parameters μ_1, μ_2, μ_3, and μ_4 are independent and identically and normally distributed. Following Hess, Train et al. (2006), we use a modified Latin hypercube sampling (MLHS) method to obtain 1000 draws for these random components. Equations 8-11 show the structural model.

$$\mathbf{z_1^* = \theta_{11} * accident + \theta_{21} * gender + \theta_{31} * socioeco_1 + \theta_{41} * socioeco_2} \tag{8}$$
$$\mathbf{+ \theta_{51} * health + \mu_1}$$

$$\mathbf{z_2^* = \theta_{12} * accident + \theta_{22} * gender + \theta_{32} * socioeco_1 + \theta_{42} * socioeco_2} \tag{9}$$
$$\mathbf{+ \theta_{52} * health + \mu_2}$$

$$\mathbf{z_3^* = \theta_{13} * disease + \theta_{23} * gender + \theta_{33} * socioeco_1 + \theta_{43} * socioeco_2} \quad (10)$$

$$\mathbf{+ \theta_{53} * health + \mu_3}$$

$$\mathbf{z_4^* = \theta_{14} * disease + \theta_{24} * gender + \theta_{34} * socioeco_1 + \theta_{44} * socioeco_2} \quad (11)$$

$$\mathbf{+ \theta_{54} * health + \mu_4}$$

In the measurement model, 14 indicators (Likert questions) are used to identify the LV. Following table 2, indicators I_{11}, I_{21}, I_{31}, I_{41} and I_{51} are used for z_1^*; for z_2^*, we used indicators I_{12}, I_{22}, I_{32} and I_{42}; for z_3^*, we used indicators I_{13}, I_{23} and I_{33}; and finally, indicators I_{14}, I_{24} were used for z_4^*. The measurement model was estimated using a continuous specification (equation 3); therefore, in addition to the γ_p parameters, we estimated Θ_p parameters of standard deviations. We compare the results of the HCM with those of a multinomial logit model (MNL).

5. Results and Discussion

The results of the MNL and HCM (choice model) are presented in table 4. We calculated the WTP (in US$) for reductions in traffic and current cardiorespiratory risks ($\beta + \alpha_r z_r^*$ divided by the cost parameter). We calculate WTP's variance through the delta method. We present the log-likelihood of the choice model and the joint model (only for the HCM).

Table 4. Estimation Results

Explanatory variables	MNL Coefficient (Robust t-ratio)	HCM Coefficient (Robust t-ratio)
ASC	-0.2086 (-2.10)	-7.3144 (-8.05)
Traffic risk	-0.0176 (-9.94)	-0.0153 (-7.79)
Current cardiorespiratory risk	-0.0003 (-0.86)	-0.0023 (-3.46)
Future cardiorespiratory risk	-0.0006 (-5.40)	-0.0002 (-2.13)
Cost	-0.0001 (-7.96)	-0.0001 (-6.74)
Traffic Controllability	-	0.0058 (4.24)
Traffic Concern	-	-0.0496 (-10.45)
Cardiorespiratory Controllability	-	-0.0001 (-0.22)
Cardiorespiratory Concern	-	-0.012 (-8.24)
Traffic WTP (in US$)	0.2562 (0.1666; 0.3459)	0.2651 (0.1750; 0.3552)
Current cardiorespiratory WTP (in US$)	0.0051 (-0.0069; 0.0171)	0.0211 (0.0055; 0.0368)
Future cardiorespiratory WTP (in US$)	0.0085 (0.0043; 0.0127)	0.0033 (-0.0003; 0.0069)
Log-likelihood choice model	-7299.914	-5140.683
Log-likelihood hybrid model	-	-21369.42
N	775	775

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

In the MNL, all coefficients are statistically significant except for current cardiorespiratory risk. They have the expected negative signs, that is, a higher risk level implies a negative change in the utility of the individual. The negative sign in the alternative-specific constant means that choosing the status quo (higher risk) negatively affects utility. The mean marginal WTP using this model is US$ 0.26 for reductions in the probability of premature death related to traffic risks, whereas the WTP for cardiorespiratory risks is not statistically significant. In the HCM, the parameters of traffic risk, cost, and current and future cardiorespiratory risk are statistically significant, also with the expected sign. The alternative-specific constant is statistically significant and has a negative sign. Changes in the statistical significance (or signs) of explanatory variables are not uncommon when one uses an HCM. Bouscasse (2018) finds these common divergences and suggests that an HCM can detect the true role of the variables.

Regarding LVs, traffic controllability is statistically significant and has a positive sign. This sign accords with the literature, that is, if people believe that they have more control over the possibility of a traffic accident, then their WTP for risk reduction decreases. Conversely, the controllability of cardiorespiratory risks is not statistically significant. The LVs related to concern about the risks are statistically significant for both types of risk. There is a negative effect of concern and controllability on the probability of choosing the status quo. This is meaningful; the higher the concern about traffic or cardiorespiratory risk, the higher is a respondent's WTP for risk reductions. Note that the effect of concern about traffic and cardiorespiratory risks is higher than the effect of the attribute itself, showing the implications of including LVs (and the use of an HCM) to improve our understanding of people's preferences.

The results of the structural model are shown in table 5. The binary variable *traffic accident* is statistically significant in the regression for *concern* and has a positive sign, which implies that the experience of a traffic accident in the last three years increases one's concern about traffic risks. On the other hand, for cardiorespiratory risks, *cardiorespiratory disease* negatively impacts the reported control of these risks. Males feel a higher sense of control related to traffic and cardiorespiratory risks than females and have less concern about these risks. Regarding cardiorespiratory controllability, the gender of the individual has no significant effect. The lowest socioeconomic level (*socioeconomic 1*) is statistically significant in each LV. Individuals who belong to this socioeconomic level show a deeper concern about traffic risks, and more control over them, and less concern about and control over cardiorespiratory risks, than the wealthiest group. The middle socioeconomic level (*socioeconomic 2*) is not statistically significant across the different LVs. Finally, self-reported health status is statistically significant only for traffic risks. The higher the self-reported health status is, the lower the perceived concern about traffic risks and controllability over them.

Table 5. Results of the Structural Model

	Traffic controllability	**Traffic concern**	**Cardiorespiratory controllability**	**Cardio-respiratory concern**
Explanatory variables	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)	Coefficient (Robust t-ratio)
Traffic controllability				
Traffic accident	-0.046 (-0.49)	0.4507 (9.30)	-	-
Cardiorespiratory disease	-	-	-0.1862 (-2.04)	0.0513 (0.89)
Gender	0.3885 (3.95)	0.483 (7.15)	0.1003 (1.08)	-0.217 (-3.44)
Socioeconomic 1	0.3084 (2.73)	0.7986 (9.52)	-0.222 (-2.14)	-0.1474 (-2.74)
Socioeconomic 2	0.1319 (1.01)	0.1277 (1.54)	-0.0597 (-0.53)	0.0658 (1.68)
Health status	-0.0855 (-3.6)	-0.145 (-6.37)	0.0198 (0.81)	0.0134 (1.27)

Source: Author's elaboration.

Table 6 shows the measurement models. The impact of the γ_p parameters on the LVs are statistically significant and positive for almost all the attitudinal indicators, the exceptions being the indicators for cardiorespiratory concern. This implies that a higher value in the latent variable identifies individuals who are more concerned about or have more sense of control over the risk.

Table 6 also shows the estimated values for Θ_p standard deviations; their values are approximately one, which is reasonable because we specify a normal density in the measurement model.

Table 6. Results of the Measurement Model

Traffic controllability	**Coefficient (Robust t-ratio)**	**Traffic concern**	**Coefficient (Robust t-ratio)**
γ_{11}	1.0346 (22.06)	γ_{12}	-0.5962 (-6.62)
γ_{21}	1.06 (23.05)	γ_{22}	-0.5208 (-5.71)
γ_{31}	1.2983 (27.59)	γ_{32}	-0.6194 (-6.89)
γ_{41}	1.3742 (29.88)	γ_{42}	-0.449 (-6.00)
γ_{51}	1.3977 (29.98)	Θ_{12}	1.2296 (26.43)
Θ_{11}	0.9721 (25.06)	Θ_{22}	1.1753 (24.98)
Θ_{21}	0.9372 (24.91)	Θ_{32}	1.1369 (22.95)
Θ_{31}	0.6812 (18.24)	Θ_{42}	0.9608 (22.51)
Θ_{41}	0.5609 (14.15)		
Θ_{51}	0.6017 (14.63)		
Cardiorespiratory controllability	**Coefficient (Robust t-ratio)**	**Cardio-respiratory concern**	**Coefficient (Robust t-ratio)**
γ_{13}	1.0744 (22.51)	γ_{14}	0.6948 (10.84)
γ_{23}	1.0116 (22.76)	γ_{24}	0.6841 (10.94)
γ_{33}	1.2461 (33.72)	Θ_{14}	0.7734 (22.79)
Θ_{13}	0.9001 (21.38)	Θ_{24}	0.8032 (19.82)
Θ_{23}	0.9584 (25.17)		
Θ_{33}	0.8124 (18.07)		

Source: Author's elaboration.

In the HCM, the mean marginal WTP for a reduction of premature death in traffic risks is US$ 0.2651, with a confidence interval ranging between US$ 0.1750 and US$ 0.3552. On the other hand, the mean marginal WTP for current cardiorespiratory risks is US$ 0.0211, with a confidence interval ranging between US$ 0.0055 and US$ 0.0368. The WTP for future cardiorespiratory risks is not statistically significant. These results provide new evidence on the interaction of self-perceived control and risks, stressing the inverse relationship between control and WTP for risk reductions (Olofsson, Gerdtham et al. 2019) and the positive relationship between concern and WTP (Carlsson, Daruvala et al. 2010).

Following GreenLabUC (2014), 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 range (P_{re}), and multiplying by a weighting rate that represents each of n individuals in the sample.

$$\mathbf{VSL = 12 * P_{re} * \sum WTP * \frac{w_n}{\sum w_n}} \tag{10}$$

Table 4 presents the marginal WTPs for reductions in traffic and current and future cardiorespiratory risks estimated by the MNL and HCM. The population in each age segment in Santiago is 1.9 million individuals for the age range between 25 and 44 years old, 1.5 million for the segment aged between 45 and 64 years, and 0.6 million for those aged 65+ years (INE 2014). Table 7 summarizes our estimated VSL for each model with their respective lower and upper bounds; additionally, in parentheses, we present values in 2017 dollars[7]. For traffic, when we use the MNL, the VSL is US$ 4.58 million; when using HCM, this value rises to US$ 4.73 million. For reductions in current cardiorespiratory risks, using MNL, the VSL is not statistically significant, but using HCM, the VSL is US$ 0.38 million. Conversely, for future cardiorespiratory risks, the VSL is not statistically significant in the HCM, but it is significant in the MNL, with a value of US$ 0.15 million.

Table 7. VSL Calculated for MNL and HCM

	MNL	HCM
Traffic VSL (in US$) average	4576329 (5206081)	4734639 (5386176)
Traffic VSL (in US$) LB	2975234 (3384658)	3125011 (3555046)
Traffic VSL (in US$) UB	6177424 (7027504)	6344270 (7217310)
Current cardiorespiratory VSL (in US$) average	-	378232 (430281)
Current cardiorespiratory VSL (in US$) LB	-	98510 (112066)
Current cardiorespiratory VSL (in US$) UB	-	657954 (748496)
Future cardiorespiratory VSL (in US$) average	151259 (172518)	-
Future cardiorespiratory VSL (in US$) LB	76275 (86772)	-
Future cardiorespiratory VSL (in US$) UB	227023 (258264)	-

Source: Author's elaboration. LB = Lower Bound, UB = Upper bound.

Although the main aim of our article is not to compare VSL values but to assess the incorporation of LVs in the estimation of VSL, we present a brief comparison of these values with other estimates in the literature. Rizzi and De La Maza (2017) review VSL estimates in Chile, finding a range between US$ 0.227 million and US$2.096 million (2017 values). Their upper value is an estimate from the OECD. (2012), and it is adjusted to real terms by Roy and Braathen (2017) to US$ 2.5 million. The values of both Parada-Contzen, Riquelme-Won et al. (2013) and GreenLabUC (2014) are not included in that article. Two other papers were published in the last two years, Mardones and Riquelme (2018) and Parada-Contzen (2019). Therefore, using all

[7] We used World Bank data to adjust the VSL estimations https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=CL

available estimates, the range of VSL estimates for Chile is between US$ 0.225 million and US$ 6.40 million[8].

In particular, the values provided by Parada-Contzen, Riquelme-Won et al. (2012) (US$ 5.7 million without endogeneity correction and US$ 15.7 million with the correction), Mardones and Riquelme (2018) (US$ 1.48 million without endogeneity correction and US$ 4.85 million with the correction) and Parada-Contzen (2019) (average value of US$ 3.96 million), which were estimated using an RP approach, are close to our estimates. In addition, GreenLabUC (2014) estimated several specifications, including an MNL with panel effects and correlation between alternatives with a VSL of US$ 5.3 million and a standard MNL (identical to our specification but with the full sample), where they obtain a VSL of US$ 6.40 million. Unfortunately, a comparison with other SP applications is inappropriate since, as GreenLabUC (2014) correctly notes, the previous values of VSL for Chile using SP were outdated, from studies conducted between 1999 and 2002, and used convenience sample.

In international terms, Dekker, Brouwer et al. (2011) summarize the VSL estimates of 26 countries to perform a meta-analysis. They calculate a mean of US$ 2.4 million (US$ 3.2 million in real 2017 terms), with a confidence interval ranging between US$ 1.1 and US$ 4.7 million for traffic risks (between US$ 1.47 and US$ 6.26 million in real 2017 terms), and for general risks (which includes air-related risks), a mean VSL of US$ 7.5 million (US$ 10 million in real 2017 terms), with a confidence interval ranging between US$ 3.0 and US$ 15.3 million (between US$ 4.0 and US$ 20.1 million in real 2017 terms). Hoffmann, Krupnick et al. (2017) conduct a series of SP studies to improve the values used to transfer benefits. The mean value ranges between US$ 0.632 million in China to US$ 5.2 million in France (between US$ 0.646 and US$ 5.31 million in real 2017 terms). Lindhjem, Navrud et al. (2011) conduct a global meta-analysis of SP-based VSL estimations, finding a mean VSL of US$ 7.4 million (US$ 9.6 million in real 2017 terms). Finally, Viscusi and Masterman (2017) report values for 189 countries, with a range between US$ 0.045 million and US$ 18.3 million in 2017 dollars, assigning a mean value of US$ 1.2 million to upper-middle-income countries.

Therefore, while our VSL estimates for traffic risk reductions are in the upper range of the values estimated for Chile, they are on average in accord with the estimates suggested in the meta-analysis of Dekker, Brouwer et al. (2011). The only unusual results are the VSL of current and future cardiorespiratory risks, which are in the lower tail of the international estimates.

[8] There are some values outside this range; for example, Parada-Contzen et al. (2013) report a VSL corrected by endogeneity that is near US$ 15.7 million. However, we only include the most general VSL reported in each article.

Returning to the aim of this paper, we verified that it is feasible to include LVs in the estimation of VSL through an HCM. Three out of four LVs were statistically significant, and the direction of their impact was as expected. Nevertheless, it is necessary to consider that the cost of estimating these models is higher than that of conventional models (Mariel and Meyerhoff 2016). The estimation time ranges from a couple of seconds in the MNL to many hours in an HCM. Additionally, it is necessary to test several starting points to ensure that our estimates are not the product of just one of the many possible local maxima. Also, it is relevant to test a sufficiently large number of random draws in the structural model because, in our experience, the results are volatile with a low number of draws.

6. Conclusions

In this article, we estimate the WTP and VSL for the population of Santiago, Chile using variables that capture the attitudes and perceptions of individuals about traffic and cardiorespiratory risks, specifically self-perceived control and concern, using the framework provided by hybrid choice models. Using this approach, we can make explicit the way in which latent variables affect the WTP for risk reductions. In our application, the effect of concern about traffic and cardiorespiratory risks is even higher than the effect of the attribute. This result highlights one of the main contributions of the HCM. Moreover, as also highlighted by Bouscasse (2018), we verify some changes in the statistical significance of some variables when we move from the classical approach to the HCM.

Despite the increase in the complexity of the estimation process, we conclude that incorporating LVs into an HCM when a stated preference study is conducted is useful to explicitly understand and decompose unobserved taste heterogeneity and increase the behavioral realism of the model. To the best of our knowledge, this is the first article to explicitly incorporate attitudes and perceptions into the estimation of VSL using an HCM framework. We use the most recent SP data collected in Chile and generate further evidence on the relationship between controllability and concern with the valuation of risk reductions.

There are several 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). Finally, there is an interesting debate that we do not cover in this paper regarding the policy implications of the incorporation of LVs in estimating VSL.

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