The effect of risk context on the Value of a Statistical Life

A Bayesian meta-model

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Abstract

This paper examines to what extent variations in the value of statistical life (VOSL) can be explained by the context in which these values are elicited. In a meta-analysis of 27 international stated preference studies a Bayesian model is estimated regressing contingent values for mortality risk reductions originating from three different risk contexts on risk, respondent and study characteristics. Evidence of contextual effects is found, most notably a higher willingness to pay (WTP) for reducing mortality risks caused by air pollution relative to improving road safety. These contextual effects can be decomposed into two parts. First, the size of the applied risk reductions, which differs between contexts and can be controlled for in and out of context benefits transfer. Second, an additional WTP premium exists depending on the specific risk context. Combined with study and preference heterogeneity detected across studies, the latter effect may cause serious distortions in benefits transfer between risk contexts.

JEL classifications: C11, I18, Q51, Q53

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1. Introduction

Benefits transfer (BT) practices in the field of risk reduction often involve the transfer of 'out of context' values. That is, values elicited for one risk source are applied in a different risk context due to the limited availability of context specific values. For instance, the US Environmental Protection Agency (EPA) combines economic valuation studies of occupational and traffic related mortality risks in order to generate an economic value for prevented premature deaths in environmental contexts (US EPA 2000). The latter value for reductions in mortality risk, which is commonly referred to as the value of statistical life (VOSL), plays an important role in the total benefits from environmental policy (Alberini 2005). However, using valuation studies from multiple risk contexts for BT purposes is a risky business. The psychology literature puts forward a number of arguments why there may be a difference in willingness to pay (WTP) for the same risk reduction in different risk contexts (Slovic 1987). In particular, different combinations of risk perception and the population at risk are expected to result in a significant difference in stated WTP for similar risk reductions in different contexts. Hence, (not) adjusting VOSL estimates in BT practices for the context in which risk values have been elicited may have serious implications for policy evaluation. Since 1999, the US EPA applies the same default VOSL (adjusted for inflation) as an input for Cost Benefit Analysis (CBA), without making adjustment for individual and risk characteristics (Dockins et al. 2004). The default VOSL of $6.1 million dollar is based on 26 valuation studies in the context of road safety and wage compensation. An application of this estimate to the evaluation of the Clean Air Act and its amendments shows that 80 percent of the total benefits can be attributed to reductions in mortality risk (Alberini 2005).

Reviews by Rowlatt et al. (1998) and Revesz (1999) propose adjustment factors for transferring VOSL estimates from road safety to air pollution, based on specific risk characteristics in each context. Both reviews predict a higher VOSL value for air pollution compared to road safety. However, empirical evidence of the effect of risk context on WTP for reductions in mortality risk is limited and mixed (Tsuge et al. 2005;Vassanadumrongdee and Matsuoka 2005). Due to this mixed empirical evidence, the U.K. Health Department refrains from applying BT of VOSL values from road safety to the air pollution context (Dunn 2001). On the contrary, the Science Advisory Board-Environmental Economics Advisory Committee (SAB-EEAC) advised the US EPA in the year 2000 not to adjust its default VOSL value for risk and population characteristics, including context, on the same grounds (Dockins et al. 2004). More recently, the EPA commissioned a group of experts to review its approach to mortality risk valuation and examine whether the default VOSL should be adjusted. The expert group questions the existence of a single VOSL, suggesting corrections for population and risk characteristics. In addition, they consider meta-analysis an appropriate method to examine variations in VOSL estimates (Allen et al. 2006). Existing VOSL meta-analyses, however, combine estimates derived from hedonic-wage (HW) and contingent valuation (CV) studies (de Blaeij et al. 2003;Elvik 1995;Kochi et al. 2006;Miller 2000;Mrozek and Taylor 2002;Viscusi and Aldy 2003). The expert group regards the derived estimates in both types of studies as distinctly different and suggests a separate analysis for both valuation methods. Furthermore, in the economic literature, including HW and CV studies, substantial ambiguity exists regarding the procedures for eliciting and estimating the VOSL. Hence, the observed variation in VOSL estimates may to a certain extent also be a result of unobserved heterogeneity across studies, as respondents' risk perceptions and preferences are likely to be affected by differences in study design.

To date, there does not (yet) exist a thorough empirical analysis covering the relevant recent literature with respect to the effect of risk context on VOSL. To fill this gap, we present a meta-analysis on the VOSL explicitly addressing the effect of risk context on stated WTP for different mortality risk reductions. More specifically, the risk contexts considered in this paper are air pollution, road safety and general 'context free' mortality risk. Our main objective is to examine to what extent variations in WTP for mortality risk reductions can be explained by the context in which the values are elicited besides study and sample characteristics. We analyze elicited values for mortality risk reductions in a Bayesian framework suitable for relatively small sample sizes (Moeltner et al. 2007;Moeltner and Woodward 2008). The model we present takes into account the concerns of the aforementioned expert group (Allen et al. 2006) with respect to study heterogeneity and only includes CV studies. Furthermore, we analyze the predictive densities for the three risk contexts, hereby illustrating the potential consequences of out of context BT.

The remainder of this paper is organized as follows. Section 2 discusses the theoretical foundations and available empirical evidence of the expected difference in WTP values between mortality risk contexts. Section 3 presents a description of the econometric model, followed in Section 4 by a presentation and discussion of the database. Section 5 presents the results of the Bayesian meta-model, while its implications for BT practices are discussed in Section 6. Finally, Section 7 concludes and provides recommendations for the use of VOSL estimates in future policy analysis.

2. VOSL and risk context

2.1 Theoretical foundations

The most commonly used concept to value reductions in mortality risk is the VOSL. A VOSL does not put a value on an individual's life, but describes the rate at which people are willing to trade off money income for reductions in mortality risk (Alberini and Chiabai 2007). Equation (1) describes this marginal rate of substitution, where V denotes expected utility, q the probability of dying and W current wealth. If, for example, a disease is expected to kill 10 out of every 100,000 people and preventive measures can be taken to reduce the probability of dying to 8 out of every 100,000, then the VOSL is calculated by dividing the amount of money people are willing to pay for this risk reduction by the change in probability (Δq=2/100,000). In CBA, the concept of VOSL is used as a measure to identify the value of a random saved life. Trade-offs made by individuals between safety and wealth are implicitly guided by preferences and perceptions towards mortality risk. The latter implies that an individual's WTP and hence the VOSL may not be independent of the risk context.

$$VOSL = \frac{\frac{\delta V}{\delta q}}{\frac{\delta V}{\delta W}} \approx \frac{\Delta W}{\Delta q} = \frac{WTP}{\Delta q} \qquad (1)$$

We can describe this individual WTP by equation 2 as a function of personal (P) and risk characteristics (R). The latter is a function of both exogenous risk R^{exo}, over which an individual has no control, and endogenous risk R^{end}, that is, the level of self-protection against the risk involved (Shogren and Crocker 1991). Since the probability of dying affects WTP directly through R, and the transformation of WTP into the VOSL, we primarily focus on explaining variations in WTP across contexts. The shape and level of the WTP function are determined by an individual's risk perception and preferences for the mortality risk faced. Risk perception is defined as the subjective judgment of a particular event, outcome or happening in terms of likelihood of occurrence and its consequences. A broad range of literature addresses the effect of personal characteristics, e.g. age, income and health, on WTP (Alberini et al. 2004;Krupnick 2007). It should be noted that the debate on the exact relationship between these personal characteristics and WTP has not yet been settled, due to scarce and sometimes ambiguous results from empirical analyses (Evans and Smith 2006) [1]. The analysis presented here restricts itself to the effect of risk characteristics, in particular risk context, on an individual's WTP through risk perception and is driven by the proposed revision of VOSL measures by the US EPA.

[1] Another issue is that the population at risk differs between risk contexts. Health effects from air pollution threaten especially the elderly, while work-related health effects mainly affect people of working age. Interactions between personal and risk characteristics have not yet been examined in the current VOSL literature (Krupnick 2007).

$$WTP_i = f\left(P, R\left(R^{exo}, R^{end}\right)\right) \tag{2}$$

Slovic (1987) identifies four determinants of individual risk perception. The first determinant is *awareness and knowledge* of the risk to which individuals are exposed. An individual has to be aware of a risk before she can form a judgment about it. In the same vein, people tend to overestimate risks that receive a lot of media attention (Slovic 2000). The second determinant, *severity*, refers to the degree of harm experienced from a 'bad' outcome. The meta-analysis presented here covers a single risk indicator, i.e. mortality. Hereby, we keep the 'objective' measurement of severity constant across observations to enable an empirical assessment of the effect of risk context on stated WTP[2]. The third determinant, *voluntariness*, reflects the degree of freedom people have to avoid a particular risk (e.g. dying from bungee jumping or in a traffic accident). The fourth determinant is the degree of *control* people have when facing a particular risk. For example, being the driver versus a passenger in a vehicle may generate a completely different feeling of safety. Similarly, the perceived control over dying in different risk contexts might influence decision-making with respect to safety measures. Since these determinants of risk perception are inherently and uniquely related to each risk context, risk perceptions are likely to differ between contexts. As a consequence, WTP values for risk reductions of similar size are expected to differ across contexts.

2.2 Empirical evidence

Of interest here are contextual effects, not so much the effect of each of Slovic's (1987) four determinants of risk perception on WTP. However, these determinants help to characterize the risk context and are used below to structure the presentation of the available empirical evidence below. Exposure to mortality risk caused by air pollution is generally perceived as less voluntary and less controllable than road safety (Revesz 1999;Rowlatt et al. 1998). Based on these differences, both studies predict a higher WTP for reductions in mortality risk in the case of air pollution than for similar risk reductions in the case of road safety[3]. Cookson (2000) confirms the importance and negative effect of voluntariness and locus of control on stated WTP based on focus group discussions related to prioritizing and valuing risk reductions in six policy contexts. MC Daniels et al. (1992) introduce a new determinant, i.e. personal exposure, and observe an increase in WTP if respondents are personally exposed to a particular mortality risk. Subramanian and Cropper (2000) confirm both the importance of personal exposure and the negative effect of degree of control on preferences and WTP for life saving programs. Voluntariness is, however, found to be insignificant. Similar results are found by Chilton et al. (2002). They show that the extent of personal exposure is a significant determinant of WTP, but not locus of control and voluntariness. Savage (1993) finds a negative rela-

2 The measurement unit (reductions in the probability of dying from a particular cause) is comparable within and between contexts. A broad range of benefit estimates for mortality risk reductions is available from different risk contexts, which are directly applied in BT-functions by policy agencies (Sunstein 2004).

3 Both studies also expect a higher WTP for reductions in air pollution, because environmental causes of death are often associated with a dread of cancer.

tionship
between awareness and knowledge of the risks people are exposed to and their WTP.

Vassanadumrongdee and Matsuoka (2005) find comparable WTP values for mortality risk reductions for air pollution and road safety after controlling for personal exposure. Tsuge et al. (2005) observe similar negligible context effects and show that the timing of the risk reduction and personal characteristics are the main determinants of stated WTP. Beattie et al. (1998) on the other hand find a discrepancy between WTP for mortality risk reductions from road safety and domestic fires. In addition, two meta-analyses by Elvik (1995) and Miller (2000) observe, on average, a higher WTP for occupational safety than for road safety. Thus, there is evidence in the existing literature that the VOSL differs between contexts due to the effect of risk characteristics on risk perception, but consistent empirical results are lacking.

3. Econometric model

3.1 General model structure

The model structure adopted in this paper to examine contextual effects is based on Moeltner et al. (2007) and assumes that each primary valuation study represents a subgroup of people exposed to mortality risk. Hence, each study *s* represents a subpopulation of the overall population exposed to mortality risks in which individual *i* from sub-population *s* states a WTP 'y_{ijs}' for a specific reduction in mortality risk *j*. The meta-analysis focuses on a representative agent from sub-population *s*. Following equation (2), the estimated mean WTP '$\hat{y}_{js}$' is described as a function of average sub-population characteristics $\bar{\mathbf{x}}_s$, risk reduction characteristics $\mathbf{q}_j$ and a set of associated meta-parameters $\boldsymbol{\beta}_s$[4]. Given the variety in applied survey designs and analytical approaches, we model average WTP values conditional upon methodology characteristics $\boldsymbol{m}_s$.

To model unobserved heterogeneity between sub-populations, we allow a subset of the meta-parameters to vary across studies. For example, differences in perception and interpretation of risk reductions by respondents across studies may result in a study-specific parameter estimate for the size of the risk reduction. On the other hand, similarities in survey design are expected to have a common effect across studies. Thus, we incorporate the methodological variables among other variables as fixed parameters. Random parameters are indicated by $\boldsymbol{\beta}_{rs}$ and fixed parameters by $\boldsymbol{\beta}_f$. Both are sub-vectors of $\boldsymbol{\beta}_s$. Since the number of elements in $\boldsymbol{\beta}_{rs}$ is unknown a priori, we formulate a flexible model. Comparison of multiple specifications is possible, including a variance components model, a mixed coefficients model and a full random coefficients model.

The meta-regression model (MRM) is described in equation (3) where the dependent variable WTP is transformed into its natural log form. $\mathbf{z}_{js}$ denotes a row vector associated with all fixed elements $\boldsymbol{\beta}_f$ and $\mathbf{x}_{r,js}$ is a similar input vector associated with the random elements $\boldsymbol{\beta}_{rs}$. The error term ε_{js} is assumed to be i.i.d. normal. The random parameters will address heteroskedasticity and are assumed to be drawn from a multivariate normal distribution (mvn) with mean vector $\mathbf{b}$ and variance-covariance matrix $\sum$.

$$\ln\left(\hat{y}_{js} \mid \mathbf{x}_{r,js}, \mathbf{z}_{js}\right) = \mathbf{x}_{r,js}\boldsymbol{\beta}_{rs} + \mathbf{z}_{js}\boldsymbol{\beta}_f + \varepsilon_{js} \text{ with } \varepsilon_{js} \sim n\left(0,\sigma^2\right) \text{ and } \boldsymbol{\beta}_{rs} \sim mvn\left(\mathbf{b},\boldsymbol{\Sigma}\right) \qquad (3)$$

The distributional assumptions regarding the error term and elements of $\boldsymbol{\beta}_{rs}$ imply that the natural logarithm of WTP, $\ln\left(\hat{y}_{js} \mid \mathbf{x}_{r,js}, \mathbf{z}_{js}\right)$, for a specific risk reduction *j* in sub-population *s* is also normally distributed with expected value $\mathbf{x}_{r,js}\,\mathbf{b} + \mathbf{z}_{js}\,\boldsymbol{\beta}_f$ and variance $\mathbf{x}_{r,js} \sum \mathbf{x}'_{r,js} + \sigma^2$. Equation (4) describes the properties of the vector of WTP values obtained from a specific primary study. The log description in the expectation set is sup-

[4] An implicit assumption here is that each study generates consistent estimates of the underlying WTP value. To clarify the notation, vectors are represented by bold letters, matrices in capital letters and subscripts define the associated dimension(s).

pressed for notational convenience, *ns* represents the number of observations obtained from study *s* and $\mathbf{I}_{ns}$ is the identity matrix of size *ns* by *ns*.

$$\begin{aligned}
&\ln\left(\hat{\hat{\mathbf{y}}}_s \mid \mathbf{X}_{rs}, \mathbf{Z}_s\right) = \mathbf{X}_{rs}\boldsymbol{\beta}_{rs} + \mathbf{Z}_s\boldsymbol{\beta}_f + \varepsilon_s \text{ with} \\
&E\left(\hat{\hat{\mathbf{y}}}_s \mid \mathbf{X}_{rs}, \mathbf{Z}_s\right) = \mathbf{X}_{rs}\mathbf{b} + \mathbf{Z}_s\boldsymbol{\beta}_f \text{ and} \\
&E\left(\hat{\hat{\mathbf{y}}}_s \hat{\hat{\mathbf{y}}}_t'\right) = \begin{cases} \mathbf{X}_{rs}\boldsymbol{\Sigma}\mathbf{X}_{rs} + \sigma^2\mathbf{I}_{ns}, & s = t \\ 0, & \text{otherwise} \end{cases}
\end{aligned} \tag{4}$$

As $\mathbf{x}_{\mathbf{r,js}}$ enters the second moment expression in (3) and (4), the specification captures observation and study-specific heteroskedasticity. Furthermore, equation (4) denotes that intra-study observations are correlated with each other via the regressors included in $\mathbf{X}_{\mathbf{rs}}$, where a random intercept captures unobserved elements constant at the study level (Moeltner et al. 2007). Therefore, observations are no longer treated as independent.

3.2 Bayesian framework

For modeling conveniences a Bayesian estimation framework is chosen to account for possible hierarchical relationships and not having to rely on asymptotic theory under a (relatively) small sample size (Moeltner and Woodward 2008). In addition, model comparison under the specified flexible, non-nested model structure is more convenient in a Bayesian framework. Equation (5) describes the likelihood function belonging to the specified model, in which **y** represents the vector containing all WTP observations, S the total number of studies and $\mathbf{X}_\mathbf{r}$, **Z** and $\boldsymbol{\beta}_\mathbf{r}$ the stacked equivalents of the study-specific matrices from equation (4).

$$p\left(\mathbf{y} \mid \mathbf{X}_r, \mathbf{Z}, \boldsymbol{\beta}_r, \boldsymbol{\beta}_f, \sigma^2\right) = \prod_{s=1}^{S} \frac{1}{\left(2\pi\sigma^2\right)^{n_s/2}} \exp\left(-\frac{1}{\sigma^2}\left(\mathbf{y}_s - \mathbf{X}_{rs}\boldsymbol{\beta}_{rs} - \mathbf{Z}_s\boldsymbol{\beta}_f\right)'\left(\mathbf{y}_s - \mathbf{X}_{rs}\boldsymbol{\beta}_{rs} - \mathbf{Z}_s\boldsymbol{\beta}_f\right)\right) \tag{5}$$

The prior distributions for our model-parameters [$\boldsymbol{\beta}_{rs}$, $\boldsymbol{\beta}_f$, **b**, σ^2, $\sum$] are specified in equation (6). We assume that both beta vectors are drawn from a mvn distribution with a mean vector, respectively $\boldsymbol{\mu}_f$ and **b,** and covariance matrices $\mathbf{V}_f$ and $\sum$. As a Bayesian analogue to the classical random effects model, an additional layer of prior distributions is assigned to the components of the distribution on $\boldsymbol{\beta}_{rs}$. As such the model is classified as a hierarchical model and we ensure that within each study the elements of $\boldsymbol{\beta}_{rs}$ are drawn from the same distribution, but that the mean and variance are allowed to vary between studies. The mean vector **b** follows a mvn distribution with mean vector $\boldsymbol{\mu}$ and covariance matrix **V**. We select a Wishart distribution with degrees of freedom ρ and symmetric input-matrix **R** for the inverse of the covariance matrix $\sum$. Note that the latter reduces to an inverse gamma distribution in case of a single random parameter. The variance term σ^2 is assumed to be drawn from an inverse gamma (*ig*) distribution with shape parameter α and scale parameter γ.

$$\begin{aligned} &p\left(\boldsymbol{\beta}_f\right)=mvn\left(\boldsymbol{\mu}_f,\mathbf{V}_f\right)\\ &p\left(\boldsymbol{\beta}_{rs}\mid\mathbf{b},\boldsymbol{\Sigma}\right)=mvn\left(\mathbf{b},\boldsymbol{\Sigma}\right)\\ &p\left(\mathbf{b}\right)=mvn\left(\boldsymbol{\mu},\mathbf{V}\right)\\ &p\left(\boldsymbol{\Sigma}^{-1}\right)=W\left(\left(\rho\mathbf{R}\right)^{-1},\rho\right)\\ &p\left(\sigma^2\right)=ig\left(\alpha,\gamma\right) \end{aligned} \tag{6}$$

Combining these priors with the specified likelihood function when analyzing the available data results in a joint posterior distribution for the model parameters p($\boldsymbol{\beta}_f$, **b**, $\sum$, σ^2|**y**, $\mathbf{X}_r$,**Z**). The posterior density function takes in this case an inconvenient form, from which the properties can not be derived analytically. We therefore apply a Gibbs-Sampler (GS) (Moeltner et al. 2007) to obtain a set of analyzable conditional posterior distributions for the individual model parameters (Appendix A). After a sufficient number of repetitions, the draws from the conditional posterior distributions in the GS will converge to the joint posterior distribution (Gelman et al. 2004). The moments of the corresponding marginal distributions can be obtained from the series of draws for each parameter.

3.3 Welfare predictions

Forecasting the WTP for mortality risk reductions in a particular risk context based on the specified model requires the derivation of the predictive posterior distribution conditional on a set of available explanatory variables for that risk reduction. The set of (predictive) explanatory variables contains all control variables adopted in the original MRM $\left[\bar{\mathbf{x}}_p,\mathbf{q}_p,\mathbf{m}_p\right]$, denoting respectively vectors for average population, risk and methodological characteristics, which are split up in our conventional set of fixed and random coefficients $\mathbf{x}_{rp}$ and $\mathbf{z}_p$. For BT purposes, our main interest lies in the marginal predictive posterior distribution of WTP $p\left(\tilde{y}\mid\mathbf{x}_{rp},\mathbf{z}_p\right)$, which is further specified in equation 7. The original MRM-parameters [$\boldsymbol{\beta}_f$, **b**, $\sum$, σ^2] are combined in $\boldsymbol{\theta}$. Note that all data information and remaining parameter uncertainty is contained in the previously derived posterior distribution for $\boldsymbol{\theta}$. Hence, predicted WTP conditional on $\boldsymbol{\theta}$ is independent of the original data. The procedure to simulate WTP values using this predictive density is de-scribed in (Moeltner et al. 2007)

$$\begin{aligned} &p\left(\tilde{y}\mid\mathbf{x}_{rp},\mathbf{z}_p\right)=\int_\theta p\left(\tilde{y},\boldsymbol{\theta}\mid\mathbf{x}_{rp},\mathbf{z}_p,\mathbf{y},\mathbf{X}_\mathbf{r},\mathbf{Z}\right)d\boldsymbol{\theta}\\ &=\int_\theta p\left(\tilde{y}\mid\boldsymbol{\theta},\mathbf{x}_{rp},\mathbf{z}_p\right)p\left(\boldsymbol{\theta}\mid\mathbf{y},\mathbf{X}_\mathbf{r},\mathbf{Z}\right)d\boldsymbol{\theta} \end{aligned} \tag{7}$$

4. Data description

4.1 Response variable

Following the recommendations by Allen et al. (2006), we restrict the meta-analysis to VOSL studies using stated preference (SP) methods. The formulation of WTP questions in SP studies allows to capture the effect of risk context and also reduces possible embedding effects by focusing only on the valuation of mortality risks and not related morbidity effects (Schwab Christe and Soguel 1995). By including only SP studies a single Hicksian welfare measure, i.e. the compensating surplus, is taken as the response variable[5].

Relevant SP studies within the three selected risk contexts are obtained through a wide and extensive literature search described in Appendix B. A first selection criterion was to screen existing studies for a specified cause of death to identify the risk context. We further reviewed the studies on how they presented a specific risk reduction, e.g. in the form of a change in the probability of dying, or an equivalent relationship that can be converted into a probabilistic specification, such as the number of people saved from the current population, or per 100,000 people. The search and screening process initially identified 9 air pollution, 26 road safety and 10 general context related VOSL studies, both published and unpublished. Additional screening based on study characteristics described in Appendix B, resulted in a final database consisting of 27 studies reporting 7 air pollution, 71 road and 20 general mortality VOSL estimates.

4.2 Control variables

As can be observed from Table 4.1, there exists considerable variation in the VOSL within and between risk contexts. Within the air pollution, road safety and general context, the VOSL ranges respectively between 0.13 and 5.43 million, 0.66 and 33.58 million, and 0.53 and 8.91 million in 2004 PPP converted dollars. At first sight, contrary to expectations (Revesz 1999;Rowlatt et al. 1998), the VOSL in the road safety context appears to be relatively higher compared to the two other risk contexts. However, this is partly due to the smaller risk reductions within the road safety context, which result in a higher VOSL given a constant WTP. We focus on explaining variations in WTP instead of VOSL, as Section 2 highlighted that (i) risk perception primarily affects WTP, of which the VOSL is just a transformed measure, and (ii) the size of the risk reduction may influence the VOSL along two dimensions (Hammitt and Graham 1999). We select a set of control variables for risk, respondent and study characteristics to explain the observed variation in WTP for mortality risk reductions within the three risk contexts.

5 It should be noted that SP VOSL estimates are generally found to be higher compared to revealed preference estimates (de Blaeij et al. 2003). Strand (2001), however, argues that SP studies result in more stable VOSL estimates.

Table 4.1 VOSL estimates from three mortality risk contexts in 2004 PPP converted $.

Authors	Country	Public-ation year	Study year	Risk con-text	No. of esti-mates	Single estimate (x1000)	Lowest es-timate (x1000)	Highest es-timates (x1000)
(Alberini and Chia-bai 2007)	Italy	2007	2004	Air pollu-tion	1	1,902		
(Alberini et al. 2005)	Czech Re-public	2005	2004	Air pollu-tion	1	2,881		
(Hammitt and Zhou 2006)	China	2006	1999	Air pollu-tion	3		130	448
(Vassanadumrongdee and Matsuoka 2005)	Thailand	2005	2003	Air pollu-tion	2		3,493	5,426
(Andersson and Lindberg 2007)	Sweden	2007	1998	Road safety	3		1,447	4,265
(Andersson and Svensson 2008)	Sweden	2008	2005	Road safety	2		1,312	1,446
(Beattie et al. 1998) [b]	UK	1998	1995	Road safety	4		7,470	19,477
(Brabander 2006)	Belgium	2006	2005	Road safety	4		4,585	12,569
(Desaigues and Rabl 1995) [b]	France	1995	1994	Road safety	12		663	24,318
(Ghani and Faudzi 2003)	Malaysia	2003	2003	Road safety	4		693	1,682
(Hultkrantz et al. 2006)	Sweden	2006	2004	Road safety	2		2,093	5,518
(Johannesson et al. 1996) [b]	Sweden	1996	1995	Road safety	4		2,054	7,130
(Jones-Lee et al. 1983) [b]	UK	1983	1982	Road safety	14		767	13,110
(Kidholm 1995) [b]	Denmark	1995	1993	Road safety	3		8,955	13,345
(Lanoie et al. 1995) [b]	Canada	1995	1986	Road safety	2		1,860	3,329
(Maier et al. 1989) [b]	Austria	1989	1989	Road safety	6		1,832	5,056
(MC Daniels 1992) [b]	US	1992	1986	Road safety	3		9,358	33,584
(Persson et al. 1995) [b]	Sweden	1995	1993	Road safety	2		4,038	4,610
(Schwab Christe 1995) [b]	Switzerland	1995	1993	Road safety	1	13,040		
(Schwab Christe and Soguel 1996) [b]	Switzerland	1996	1994	Road safety	2		971	1,167
(Vassanadumrongdee and Matsuoka 2005)	Thailand	2005	2003	Road safety	2		4,137	5,900
(Viscusi et al. 1991) [b]	US	1991	1991	Road safety	1	10,596		
(Alberini et al. 2004)	US and Canada	2004	2000	General	4		1,015	5,214
(ExternE 2004)	UK, France and Italy	2004	2002	General	8		635	8,914
(Itaoka et al. 2005)	Japan	2005	1999	General	4		705	2,425
(Krupnick et al. 1999)	Japan	1999	1998	General	2		551	1,171
(Zhang 2002)	China	2000	1999	General	2		533	975

[b] studies also included in (de Blaeij et al. 2003)

Risk characteristics

From a theoretical perspective, the WTP function is assumed to be linear for small changes in mortality risk. Therefore, Hammitt and Graham (1999) stipulate that VOSL estimates are constant due to a proportional increase in WTP compared to the size of the risk reduction. Most of the studies in the database indeed indicate that WTP increases if the size of the risk reduction increases. The observed increase in WTP is, however, less than proportional in almost all studies. Hence, we include a control variable for the size of the risk reduction. Both the size of the risk reduction and the baseline risk level are described in this meta-analysis by the number of (prevented) annual deaths per 100,000 people.

WTP for a risk reduction is likely to increase with higher baseline mortality risks due to a '*dead anyway'* effect, while at low risk levels individuals may tend to neglect their risk exposure, thereby reducing marginal WTP (Sunstein 2004). Empirical evidence regarding the effect of baseline risk on WTP is limited. De Blaeij et al. (2003) observe a positive effect of baseline risk on VOSL. In addition, we define two dummy variables for respectively air pollution and road safety and set general mortality risk as the baseline context.

Respondent characteristics

An extensive body of literature discusses the adjustment of VOSL measures for age, income and health (e.g. Alberini et al. 2004;Krupnick 2007;Sunstein 2004). In addition, in the road safety context, men are found to underestimate the risk they face compared to women (Andersson 2007). However, inconsistent reporting of respondent characteristics across studies prevents us from including most of them in the meta-regression. For example, average age can only be retrieved for 47 estimates in our sample.

Methodological characteristics

Several question formats are used in the literature to elicit WTP for mortality risk reductions, primarily open-ended (OE), payment cards (PC) and dichotomous choice (DC) questions. Contrary to the OE questions, the other elicitation methods provide respondents with one or more value cues. Everyday market decisions are based on given price information and hence the DC and PC formats are argued to better simulate real market conditions. Common findings in the literature are that DC has a positive effect on WTP (e.g. Bateman et al. 1995). We use dummy variables to describe the elicitation method used in each study, where the OE format is treated as the baseline category.

The way of describing and presenting the mortality risk in the survey is also expected to affect risk perception and the interpretation of the good to be valued. To control for the effect of risk communication, we include a dummy variable, which has the value one for estimates based on a number of saved lives formulation and zero if formulated in terms of probabilities. Graphical devices are often used to communicate the change in risk to respondents. Common used formats are 'risk ladders' and cards displaying 'dots' (Corso et al. 2001). Both devices are accounted for in the meta-analysis through dummy variables. Another dummy variable is included to capture the effect of formulating the valuation question in terms of willingness to accept compensation (WTAC) instead of WTP. The literature indicates that WTAC for risk increases is higher than WTP for a similar risk reduction, because people do not have to consider their budget constraint and there may be an endowment effect under WTAC. Since WTAC questions are concerned with increases in risk, absolute changes in risk levels are used in the analysis.

Private goods only affect the individual through their exclusivity and excludability characteristics, whereas a public good usually does not posses these characteristics. Some studies offer private goods that reduce the risk to all household members and car passengers. As the private risk reductions directly relate to the individual (i.e. personal risk), a lower WTP for public goods is expected. Moreover, a higher WTP is expected for private goods also protecting other household members or car passengers. If the risk reduction is presented as a public good or involves the protection of additional household members, this is controlled for by dummy variables.

In order to correct for the skewness of the WTP distribution, several studies use trimmed means, excluding the highest and lowest observations. As a result, mean values may be closer to median values. A more conservative estimate (negative effect on mean WTP) is expected when trimming mean values. We include a dummy variable in the meta-analysis for trimmed estimates. A last set of dummy variables is included to control for possible differences between the continents in which the studies were conducted: Asia, Europe and North-America (Miller 2000). Europe is used as the baseline category in the analysis.

5. Meta-analysis results

In this section, we analyze the set of 98 WTP estimates for mortality risk reductions originating from three distinct mortality risk contexts and examine whether a systematic variation exists in WTP across contexts. We expect unobserved heterogeneity to manifest itself in the MRM primarily through random effects for the constant and the size of the risk reduction (DELTA), due to differences in public understanding of risk reductions (Allen et al. 2006). Respondent personal interpretation of the presented risk reductions, partially influenced by the study design, is likely to influence preferences and the latter are therefore expected to vary across studies. Hence, the level of WTP may vary between studies and in line with this the responsiveness of WTP to the size of the risk reduction, which is reflected by these two random variables.

Table 5.1 provides an overview of the descriptive statistics for the included control variables[6]. The mean values for the methodological dummy variables, varying between 5 and 25% of all observations, are illustrative for the wide variety in study designs. Furthermore, road safety forms the lion's share of all observations. In the empirical analysis we use the natural log transformations of WTP and DELTA, as they provide a better model fit in the MRM. Both variables also display substantial variation, most notably the application of smaller risk reductions in the road safety context.

Table 5.1 Descriptive statistics for 98 observations in three risk contexts

Variable name	Description	Mean	St. Dev	Min.	Max.	N
WTP	Natural log of mean WTP (2004 PPP $)	5.428	0.929	3.135	7.522	98
WTAC	Dummy variable, value=1 if WTAC questions were asked, 0 for WTP questions	0.061	0.241	0	1	98
ASIA	Dummy variable, value=1 if study was carried out in Asia, 0 otherwise	0.194	0.397	0	1	98
AIR	Dummy variable, value =1 if the study concerns the air pollution context, 0 otherwise	0.071	0.259	0	1	98
ROAD	Dummy variable, value =1 if the study concerns the road safety context, 0 otherwise	0.724	0.449	0	1	98
DELTA	Absolute change in the risk level denoted in x people saved per 100,000	14.459	21.218	0.09	100	98
HH_EXP	Dummy variable, value=1 if the good affecting the whole household or all passengers, 0 otherwise	0.082	0.275	0	1	98
PUBLIC	Dummy variable, value=1 if risk reduction is in the form of a public good, 0 otherwise	0.255	0.438	0	1	98
LIVES	Dummy variable, value=1 if WTP questions were formulated in # of lives saved, 0 for probabilities	0.214	0.412	0	1	98
LADDER	Dummy variable, value=1 for using risk ladders to communicate risk levels, 0 otherwise	0.061	0.241	0	1	98
TRIMMED	Dummy variable, value=1 if trimmed means are used, 0 otherwise	0.173	0.381	0	1	98

6 Baseline risk levels are not included in the final specification due to multi-collinearity problems. Furthermore, the variables 'dots', PC, DC and North-America are also excluded as they do not affect WTP. Dummies for Asia and other study specific characteristics are expected to partially pick up effects for some of the respondent characteristics like income. We did not detect a publication bias in our sample.

Turning to the MRM results in Table 5.2, four models are estimated, differing in the number and nature of random variables. MRM 1 tests the existence of a common context effect and ignores possible heteroskedasticity in preferences for risk reductions across sub-populations by including fixed coefficients only. MRM 2 treats the constant as a single random variable and MRM 3 the size of the mortality risk reduction (DELTA). In model 4 we specify both the constant and DELTA as random variables, thereby introducing randomness in WTP through both mean WTP levels and one of the main explanatory variables controlling for sensitivity to scope. The last three models are of particular interest for this paper for contrasting context and heterogeneity effects.

The first column for each MRM in Table 5.2 displays estimates for the mean of the posterior distribution for each parameter, the second column provides standard deviations of these distributions, and the third column reports numerical standard errors (NSE's) for the posterior means. These NSE's are adjusted using Geweke's (1992) proposed correction method for autocorrelation generally present in Markov-Chain draws. The selected prior values in the analysis are $\boldsymbol{\mu}_f=0$, $\mathbf{V}_f=10*\mathbf{I}_{kf}$, $\boldsymbol{\mu}=0$, $\mathbf{V}=10*\mathbf{I}_{kr}$, $\alpha=\gamma=1/2$, $\rho=k_r$ and $\mathbf{R}=(1/k_r)*I_{kr}$ where k_f and k_r refer respectively to the number of fixed and random coefficients. Hereby, a set of relatively non-informative priors is specified, such that the shape and location of the posterior distributions are determined for the major part by the actual data. The starting values for **b** and σ^2 in the GS are taken from standard OLS estimation results of the specified model. For $\sum$ we use the identity matrix as a starting value. Every run of the GS consists of 50,000 burn-in replications and 10,000 maintained draws. To assess convergence of the GS, Geweke's (1992) convergence diagnostic is applied.

Table 5.2 Bayesian estimation results for different meta-regression models

	Model 1 Fixed effects			**Model 2** Random constant			**Model 3** Random DELTA			**Model 4** Random Constant and DELTA		
	Post. Mean	Post std.	NSE	Post. Mean	Post std.	NSE	Post. Mean	Post std.	NSE	Post. Mean	Post std.	NSE
RE means												
Constant	-	-	-	5.615	0.226	0.010	-	-	-	5.300	0.436	0.017
DELTA	-	-	-	-	-	-	0.296	0.066	0.002	0.336	0.118	0.002
FE means												
Constant	5.687	0.238	0.002	-	-	-	5.574	0.186	0.004	-	-	-
WTAC	0.509	0.254	0.003	0.470	0.112	0.001	0.319	0.114	0.001	0.252	0.108	0.001
ASIA	-1.212	0.175	0.002	-1.192	0.111	0.003	-1.326	0.113	0.001	-1.198	0.273	0.008
AIR	-0.058	0.258	0.003	-0.094	0.140	0.003	-0.313	0.191	0.002	-0.410	0.406	0.014
ROAD	-0.743	0.190	0.002	-0.709	0.171	0.007	-0.655	0.141	0.002	-0.447	0.391	0.015
DELTA	0.259	0.057	0.001	0.277	0.040	0.002	-	-	-	-	-	-
HH_EXP	0.787	0.227	0.002	0.692	0.106	0.001	0.649	0.102	0.001	0.479	0.100	0.001
PUBLIC	-1.000	0.201	0.002	-1.045	0.097	0.002	-1.146	0.083	0.001	-1.159	0.073	0.001
LIVES	0.920	0.205	0.002	0.999	0.103	0.001	1.157	0.100	0.001	1.272	0.128	0.001
LADDER	0.628	0.259	0.003	0.619	0.135	0.001	0.891	0.173	0.002	0.878	0.333	0.005
TRIMMED	-0.193	0.167	0.002	-0.163	0.074	0.001	-0.224	0.065	0.001	-0.184	0.058	0.001
RE vars												
Constant	-	-	-	0.041	0.012	0.000	-	-	-	0.369	0.194	0.003
DELTA	-	-	-	-	-	-	0.041	0.012	0.000	0.186	0.071	0.001
Sigma	0.312	0.048	0.001	0.229	0.039	0.000	0.195	0.034	0.000	0.167	0.029	0.000
Model fit												
MAPE	0.076			0.076			0.078			0.084		
logML	-112.467			-128.531			-129.410			-122.746		
DIC	172.172			151.032			153.041			166.959		
LogBF	-			-16.064			-16.943			-10.279		
N	98			98			98			98		

In models 1 and 2, a negative impact of the road safety context on mean WTP is observed through the posterior mean for ROAD, whereas the level of WTP in the general mortality risk and air pollution context is more comparable. The NSE's reflect that these posterior means are estimated with high precision. Evidence of heterogeneity in the level of average WTP between studies is clearly illustrated by the posterior mean of 0.041 for the variance of the random constant and the reduction in the posterior standard deviations for all fixed coefficients in MRM 2.

With respect to the other included explanatory variables in Table 5.2, all posterior means have their expected sign. WTP increases for larger risk reductions, indicating sensitivity to scope, but less than proportional. If more people within the household benefit from the risk reduction, WTP rises as well. People are willing to pay less for mortality risk reductions presented as public goods. WTP is substantially lower in Asia, probably due to income differences between the continents. Formulating the valuation question in terms of the number of lives saved, using risk ladders to communicate the change in risk level or applying a WTAC format increases WTP. These findings are consistent across all MRMs. The use of a trimmed mean tends to reduce WTP, but this effect is not very pronounced in MRM 1 as there is still a high probability that the coefficient for TRIMMED is equal or larger than 0.

In MRM 3 we observe a substantial variation in the posterior mean for DELTA across sub-populations, suggesting there exist also differences in sensitivity to the size of the risk reduction involved (Hammitt and Graham 1999). Whilst controlling for these observed differences in sensitivity to scope across sub-populations, we still detect a lower level of WTP in the road safety context. Furthermore, the posterior mean and standard deviation for AIR show that WTP for risk reductions in the air pollution context is also lower compared to the general mortality risk context. The properties of the distributions for AIR and ROAD become very similar in MRM 4, which assumes that both the constant and DELTA are random across studies, and a clear context effect can no longer be detected. However, a context effect may still be present due to differences in the applied risk levels between contexts. The latter contextual effect can be controlled for in benefits transfer without imposing a WTP premium for a particular mortality risk context.

For model comparison, a set of classical and Bayesian goodness-of-fit measures is listed in Table 5.2. Details regarding the derivation and interpretation of these measures are found in Moeltner et al. (2007). With respect to mean absolute percentage error (MAPE), all models perform equally well around 8%. The marginal likelihood (ML) indicates the probability of observing the data given that the specified model is correct (Chib 1995). Bayes Factors (BF) compute the ratio of the marginal likelihood between two models. In Table 5.2 the logged versions of the ML's and BF's are presented and compared to MRM 1. The corresponding logged BF's of around -16 for models 2 and 3 imply that both models are almost equally likely. MRM 1 provides a better model fit than the other three models, which can partially be attributed to the inclusion of less parameters in the model for which diffuse priors are used. The introduction of vague priors reduces the joint prior probability of the entire set of parameters. To compensate for the loss in prior probability, models with more parameters need to describe the data substantially better through the likelihood function to outperform sparser models. Even though MRM 4 contains more parameters than models 2 and 3, it has a superior model fit. In terms of the BF scale reported in Kass and Raftery (1995), the superior fit of MRM 1 is labeled as 'decisive'. On the other hand, models 2 and 3 outperform models 1 and 4 in terms of the deviance information criterion (DIC), which is commonly used to compare models on their ability to predict out of sample values.

The best fit support for MRM 1 indicates that a difference in WTP exists between the road safety and the two other contexts, but not between the latter two. The risk premium increases further due to the application of smaller risk reductions in the road safety context. The results for air pollution and general mortality risk are convenient, as the general mortality risk studies were originally designed for applications in the air pollution and other environmental contexts (Itaoka et al. 2005). MRM 4, however, suggests that unobserved heterogeneity effects across sub-populations caused the context premium on air pollution and general mortality risk. It is difficult to choose between either MRM 1 or 4 as the correct model here, due to the use of diffuse priors for the additional parameters in MRM 4. Further research is needed to develop informed priors, such that both models can be better contrasted.

6. Benefits transfers

In this section we build further on the observation that context matters for WTP and illustrate its implications for BT. For this purpose, we examine and contrast the predictive distributions of both models 1 and 4 using a constructed set of hypothetical risk reductions following the common valuation design in the general mortality risk studies (Alberini et al. 2004). General characteristics of this set of studies include the use of probabilities and 'dots' to communicate risk levels, and the formulation of VOSL in terms of WTP for a private good rather than WTAC. We adopt this design for our set of hypothetical risk reductions and set all control variables except DELTA and the context dummies to zero. We specify three risk scenarios, each targeting a particular risk context, by varying the context dummies. The average risk reduction applied in each context is set to the average risk reduction applied in that context in the original set of studies.

Figure 6.1 plots the predictive distributions resulting from the hypothetical scenarios for the three contexts based on MRM 1. It confirms the main findings of Table 5.2, showing nearly overlapping distributions for WTP values in the air pollution and general mortality risk context. The mean of the predictive posterior distribution for road safety falls 17.5% below the predicted mean for the general mortality risk context, implying that WTP is likely to be underestimated in an out of context BT. As noted, policy makers can usually control for the smaller size of the risk reductions applied in the road safety context to reduce the transfer error, but also need to scale down WTP by a fixed amount in the BT function if based on MRM 1. The posterior standard deviation for ROAD in MRM 1 in Table 5.2 highlights that the exact size of this down scaling is surrounded by uncertainty. Compared to the posterior predictive distributions generated by MRM 4, which are displayed in Figure 6.2, MRM 1 provides smaller WTP confidence intervals. As a result, the probability of underestimating WTP in the road safety context is somewhat reduced, but the reliability of BT based on this model is still questionable. Unobserved heterogeneity in preferences for mortality risk reductions over sub-populations puts a limit on the transferability of WTP estimates within and between other policy contexts. Hence, less accurate predictions of WTP for mortality risk are found when accounting for study and preference heterogeneity across sub-populations, even though the predicted mean WTP in the road safety context falls 15.3% below the predicted mean for the general mortality risk context.

Figure 6.1 Predictive posterior distributions based on meta-regression model 1

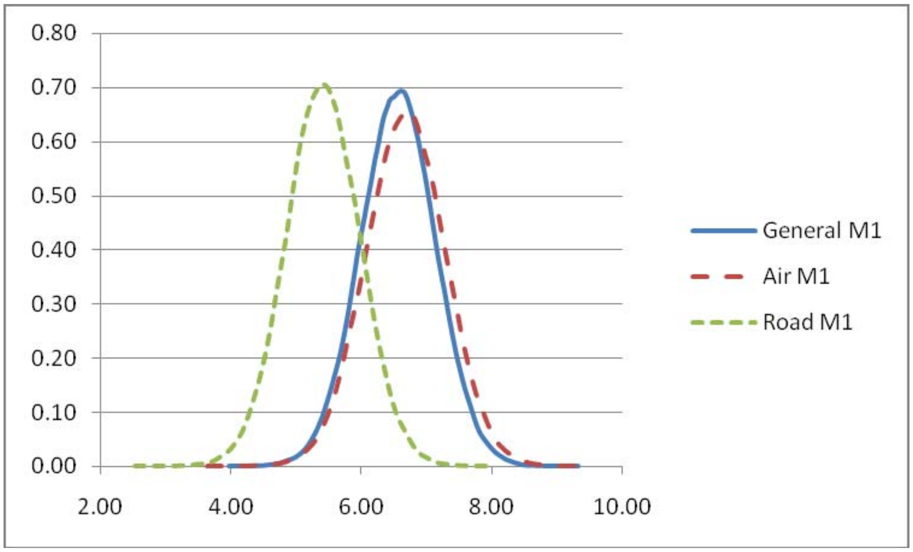
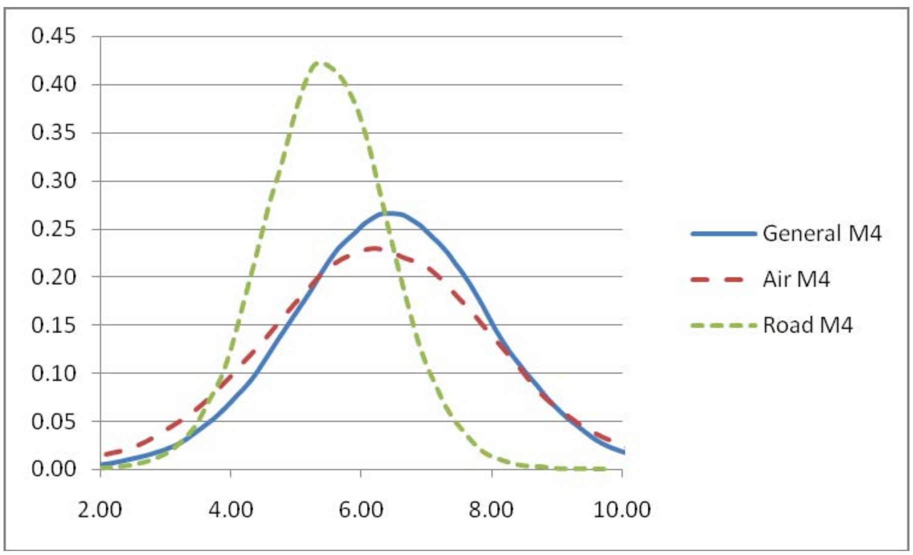


Figure 6.2 Predictive posterior distributions based on meta-regression model 4



Whether a systematic difference in preferences for risk reductions in the general mortality risk and air pollution context causes part of the variation in WTP or that preferences are random across sub-populations is, however, still open for discussion. The wide variety in applied study designs suggests that heterogeneity effects play an important role in explaining variations in WTP. A more consistent application of a particular study design is required to be able to separate these two effects. The group of general environmental mortality risk studies sets a good example in applying a coherent approach to mortality risk valuation. The current number of observations in the general mortality risk context is, however, too little to take advantage of this consistent approach.

7. Conclusions and recommendations

The meta-analysis presented here exhibits considerable variation in WTP for mortality risk reductions across and within studies in the air pollution, road safety and general mortality risk context. A Bayesian framework is applied to model (non-nested) hierarchical relationships and account for the limited number of WTP observations in the dataset without relying on asymptotic theory. Estimation results highlight that the variation in WTP values across studies can not be explained solely by controlling for risk context in combination with other risk and study specific characteristics. Indications of contextual effects are, nevertheless, present and suggest the existence of a WTP risk premium for mortality risk reductions in the air pollution and general mortality risk context relative to improving road safety. Part of this risk premium is captured through and can be controlled for in BT practices by the smaller risk reductions applied in road safety studies.

A major concern in determining the existence of systematic variation in WTP across risk contexts is unobserved study and preference heterogeneity across sub-populations. The estimated MRMs clearly show that WTP is not invariant of the elicitation method, including risk communication. Hence, the wide variety in applied study designs may be problematic and an important cause of variations in preferences for mortality risk reductions across groups of respondents. This procedural variance hampers a consistent analysis of WTP across studies, as risk levels may be, for example, more illusive to individuals exposed to the same risk using one communication method compared to another. Consistently applying a common valuation design has the advantage that less control is needed to account for the effect of methodological study characteristics. The group of general environmental mortality risk studies sets a good example in applying such a coherent approach to mortality risk valuation. The current number of observations in the general mortality risk context is, however, too little to take advantage of this consistent approach. To solve the problem of inconsistency in study design in primary valuation studies, research needs to focus much more on the development of a common mortality risk valuation design, in order to allow for a more reliable analysis of the factors affecting WTP for mortality risk reductions in different risk contexts.

Substantial inconsistencies are also observed in the reporting of respondent characteristics across studies, making it hard, if not impossible, to account for them in the estimated MRMs and thereby generate a possible omitted variable bias. Ongoing research on factors explaining variation in the VOSL suggests that a more detailed analysis of variations in WTP across different segments of the population is required and may provide additional insights. This touches upon the concerns noted by Allen et al. (2006) regarding the applicability of meta-analysis to explain variations in the VOSL. Due to the use of average WTP values, average risk, study and respondent characteristics, a lot of variability in individual WTP cannot be observed. Besides individual variability in preferences for risk reductions, the role of risk perception and interpretation based on existing communication methods deserves more attention. Heterogeneity may still play a role even if one controls for personal characteristics at average population level, due to differences in risk perception across groups. Meta-analysis may somewhat smoothen these effects, but as long as the discussion about the direction of influence of respondent characteristics on the VOSL has not been settled, the information derived through average figures may not be conclusive. Notwithstanding the mentioned caveats, this meta-analysis clearly shows that ‘out of context’ benefits transfer practices are a risky business.

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Appendix I. Conditional posterior distributions

The conditional posterior distributions for the hierarchical model specified in Section 3 from which the Gibbs Sampler takes draws for the individual model parameters are specified as follows:

$$p\left(\boldsymbol{\beta}_{f,r1} \mid \mathbf{b}_{r1}, \boldsymbol{\Sigma}_{r1}, \sigma_{r1}^2, \mathbf{y}, \mathbf{X}_r, \mathbf{Z}\right) = mvn(\boldsymbol{\mu}_{f,r1}, \mathbf{V}_{f,r1}) \text{ where}$$

$$(1) \quad \mathbf{V}_{f,r1} = \left(\mathbf{V}_f^{-1} + \sum_{s=1}^{S} \mathbf{z}_s' \left(\mathbf{x}_{rs} \boldsymbol{\Sigma}_{r1} \mathbf{x}_{rs}' + \sigma_{r1}^2 \mathbf{I}_{ns}\right)^{-1} \mathbf{z}_s\right)^{-1}$$

$$\boldsymbol{\mu}_{f,r1} = \mathbf{V}_{f,r1} \left(\mathbf{V}_f^{-1} \boldsymbol{\mu}_f + \sum_{s=1}^{S} \mathbf{z}_s' \left(\mathbf{x}_{rs} \boldsymbol{\Sigma}_{r1} \mathbf{x}_{rs}' + \sigma_{r1}^2 \mathbf{I}_{ns}\right)^{-1} \left(\mathbf{y}_s - \mathbf{x}_{rs} \mathbf{b}_{r1}\right)\right)^{-1}$$

$$p\left(\boldsymbol{\beta}_{rs,r1} \mid \boldsymbol{\beta}_{f,r1}, \mathbf{b}_{r1}, \boldsymbol{\Sigma}_{r1}, \sigma_{r1}^2, \mathbf{y}, \mathbf{X}_r, \mathbf{Z}\right) = mvn\left(\boldsymbol{\mu}_{s,r1}, \mathbf{V}_{s,r1}\right) \text{ where}$$

$$(2) \quad \mathbf{V}_{s,r1} = \left(\boldsymbol{\Sigma}_{r1}^{-1} + \frac{1}{\sigma_{r1}^2} \mathbf{x}_{rs}' \mathbf{x}_{rs}\right)^{-1}$$

$$\boldsymbol{\mu}_{s,r1} = \mathbf{V}_{s,r1} \left(\boldsymbol{\Sigma}_{r1}^{-1} \mathbf{b}_{r1} + \frac{1}{\sigma_{r1}^2} \mathbf{x}_{rs}' \left(\mathbf{y}_s - \mathbf{z}_s \boldsymbol{\beta}_{f,r1}\right)\right)$$

$$p\left(\mathbf{b}_{r1} \mid \boldsymbol{\beta}_{rs,r1}, \boldsymbol{\Sigma}_{r1}\right) = mvn\left(\boldsymbol{\mu}_{b,r1}, \mathbf{V}_{b,r1}\right) \text{ where}$$

$$(3) \quad \mathbf{V}_{b,r1} = \left(\mathbf{V}^{-1} + S \boldsymbol{\Sigma}_{r1}^{-1}\right)^{-1}$$

$$\boldsymbol{\mu}_{b,r1} = \mathbf{V}_{b,r1} \left(\mathbf{V}^{-1} \boldsymbol{\mu} + \boldsymbol{\Sigma}_{r1}^{-1} \sum_{s=1}^{S} \boldsymbol{\beta}_{rs,r1}\right)$$

$$p\left(\boldsymbol{\Sigma}^{-1} \mid \boldsymbol{\beta}_{rs,r1}, \mathbf{b}_{r1}\right) = W\left(V_{\Sigma,r1}^{-1}, v_{\Sigma,r1}\right) \text{ where}$$

$$(4) \quad v_{\Sigma,r1} = \rho + N$$

$$V_{\Sigma,r1}^{-1} = \left(\sum_{s=1}^{S} \left(\boldsymbol{\beta}_{rs,r1} - \mathbf{b}_{r1}\right)\left(\boldsymbol{\beta}_{rs,r1} - \mathbf{b}_{r1}\right)' + \rho R\right)$$

$$p\left(\sigma_{r1}^{2} \mid \boldsymbol{\beta}_{f,r1}, \mathbf{b}_{r1}, \mathbf{y}, \mathbf{X}_{r}, \mathbf{Z}\right) = ig\left(\alpha_{r1}, \gamma_{r1}\right) \text{ where}$$

$$\text{(5)} \quad \alpha_{r1} = \frac{1}{2}\left(n + 2\alpha\right)$$

$$\gamma_{r1} = \frac{1}{2}\left(\sum_{s=1}^{S}\left(\left(\mathbf{y}_{s} - \mathbf{x}_{rs}\boldsymbol{\beta}_{rs,r1} - \mathbf{z}_{s}\boldsymbol{\beta}_{f,r1}\right)'\left(\mathbf{y}_{s} - \mathbf{x}_{rs}\boldsymbol{\beta}_{rs,r1} - \mathbf{z}_{s}\boldsymbol{\beta}_{f,r1}\right)\right) + 2\gamma\right)$$

Appendix II. Literature search and database refinement

In order to find relevant stated preference (SP) studies within each risk context, a wide and extensive literature search was conducted. As a starting point, previous meta-analyses and literature overviews on VOSL were identified (de Blaeij et al. 2003;Kochi et al. 2006;Krupnick 2007;Leggett et al. 2001;Miller 2000;Mrozek and Taylor 2002;Viscusi and Aldy 2003). From these studies individual study references were obtained based upon the selection criteria that we looked for stated preference and context specific studies (e.g. cause of death being environmental, traffic related or general). Furthermore, within the retrieved studies references were checked to identify additional studies.

The second step of the literature search consisted of a keyword search in Econlit, Google scholar and EVRI using relevant keywords. These keywords were split up into three categories: (i) method, (ii) alternative names for mortality risk and (iii) context specific characteristics. An overview of the keywords used is provided below. Each search included a keyword from each category. Furthermore, we used the citations option in Google scholar to identify new VOSL studies.

	Keyword	Alternative keywords
1. Method	Stated preference	SP, survey, questionnaire
	Contingent valuation	CV, CVM
	Choice experiment	CE, CM
	Conjoint (choice) analysis	CA
	Willingness to pay	WTP, WTA
2. Risk description	Value of statistical life	VOSL, VSL
	Value of prevented fatality	VPF
	Statistical value of life	SVL
	Mortality risk	
	Risk of dying	
	Saved lives	
	Fatal	
3. Context	Air pollution	Particles, PM, air quality, sulfates
	Contaminated water	Water contamination, arsenic, blue baby syndrome, drinking water, water quality, nitrates
	Contaminated soil	Soil contamination, superfund, contaminated ground, waste site
	Environment	environmental
	Road	Traffic, transport, accident, crash

The final step in the search procedure consisted of a review of US Environmental Policy Agency reports in the National Centre for Environmental Economics (NCEE). In addition UK governmental (e.g. Chilton et al. 2004) and EU (e.g. ExternE 2004) reports were screened. Most of these reports were cross-referencing to each other and referred to studies already included in our database.

The selected studies were further reviewed regarding the way risk reductions are presented, e.g. in the form of a change in the probability of dying, or an equivalent relationship that could be converted into a probabilistic specification. The search and screening process identified 14 environmental pollution, 26 road safety and 10 general mortality risk context VOSL studies, both published and unpublished.

The identified studies were retrieved via internet, library and by contacting individual authors. Copies of Persson and Cedervall (1991) and Miller and Guria (1991) on road safety could not be obtained. Language barriers prevented the inclusion of Yamamoto and Oka (1994) in the group of environmental studies. In the general mortality risk context 2 studies were dropped due to their political sensitivity (Worldbank 2006) and the fact that a final report was not available (Joh et al. 2004).

The obtained VOSL estimates were either based on mean or median WTP values. WTP values are generally heavily skewed to the right, generating a considerable difference between mean and median WTP. Previous meta-analyses (e.g. de Blaeij et al. 2003) did not correct for this discrepancy. Considering the larger number of available mean VOSL values we focus our analysis solely on this type. As a result, another 9 studies were excluded from further analysis (Adamowicz et al. 2004;Andersson 2007; Cifuentes et al. 2000; Corso et al. 2001; Guo 2006; Hammitt and Graham 1999; Hammitt and Liu 2004; Kim et al. 2003; Parry Dziegielewska and Mendelsohn 2005; Persson et al. 2001; Wang and Mullahy 2006).

Alberini and Chiabai (2007) value mortality risk reductions for air pollution and provide 6 distinct values of statistical life for different age and health groups. Since only the respondent characteristics for the overall sample were reported, just a single VOSL estimate that describes WTP of the average respondent was included in the database. Carlsson et al. (2004) study the effect of different modes of transportation on WTP for mortality risk reductions in the road safety context. For this purpose the authors apply small changes in risk levels resulting in high VOSL values. They explicitly highlight that due to these small changes in risk levels their results should not be used for comparison and in public policy (Carlsson et al. 2004). Considering these remarks, also this study was not included in the database. Further exclusions were the study by Bhattacharya et al. (2007) in a road safety context. This study reports an average annual income level of 99,902 dollar (2004 PPP) with a standard deviation of over 93,000 dollar. The reported income level exceeds other income levels by almost a factor 2. Preliminary descriptive statistics in the general mortality risk context furthermore turned out to be highly influenced by one single study, namely Ortiz et al. (2004)[7], and was therefore also excluded as an outlier. Two other exclusions in the general mortality risk context are Giergiczny (2006) and Tsuge et al. (2005), because they did not report a baseline risk level from which the change in risk level could be calculated.

The inclusion of a single study in the contaminated water (Carson and Mitchell 2000) and soil (Alberini et al. 2007) context may was expected to hamper a robust analysis of

7 Descriptive statistics and graphical evidence are available on request from the author.

the effect of water asn another environmental risk context on WTP. The risk characteristics of the three environmental causes of death (air, soil and water) differ substantially. First, the risk reductions related to air pollution all have a direct impact on health, while a period of 25-30 years is needed before the health effects of reducing the amount of contaminants in the water are observed. Also the choice experiment by Alberini et al. (2007) covers time periods of 2-10 years. Tsuge et al. (2005) highlighted that the timing of the risk reduction is an important factor for WTP. As the air, road and general mortality risk context all concern immediate risk reductions, this was another reason to exclude the studyabout soil and water contaminants. Second, the sizes of the risk reduction are hardly comparable between the environmental sub contexts. The amount of people saved per 100,000 people in the Alberini et al. (2007) study varies between 0.1 and 0.3 a year, while air pollution studies range up to 100 people saved on an annual basis. Annual lives saved in contaminated water programs ranged between 0.04 and 8.93. Further considerations to focus primarily on the air pollution context include the application of a choice experiment in the soil context whereas all studies in the database except Alberini et al. (2007) applied a contingent valuation approach. The risk reduction in the water quality study was provided in terms of probability per 100,000 and reduction in Trihalomethanes (THM) per ppm. The latter transformation is an unknown non-linear relationship, but as baseline risks were only provided by THM per ppm and varied between presented scenarios, a baseline risk level in probability terms was difficult to derive.

Hence, the final database consists of 27 valuation studies, 4 for air pollution, 18 for road safety and 5 for general mortality risk studies. Table 4.1 provides an overview of the studies included in the final database, generating 7 environmental, 71 road and 20 general mortality VOSL estimates.