

Evidence of variable discount rates and non-standard discounting in mortality risk valuation

Mcdonald, R.I.; Chilton, S.m.; Jones-lee, M.w.; Metcalf, H.r.t.

DOI:

[10.1016/j.jeem.2016.11.005](https://doi.org/10.1016/j.jeem.2016.11.005)

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Document Version

Peer reviewed version

Citation for published version (Harvard):

Mcdonald, RL, Chilton, SM, Jones-lee, MW & Metcalf, HRT 2017, 'Evidence of variable discount rates and non-standard discounting in mortality risk valuation', *Journal of Environmental Economics and Management*, vol. 82, pp. 152-167. <https://doi.org/10.1016/j.jeem.2016.11.005>

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EVIDENCE OF VARIABLE DISCOUNT RATES AND NON-STANDARD DISCOUNTING IN MORTALITY RISK VALUATION*

Abstract

Time discounting is central to the valuation of future health and mortality risks in public sector allocative decision-making, particularly for environmental policies with delayed health impacts. Using a Risk-Risk trade-off survey, we elicit discount rates for fatality risks and establish discounting functional forms on both a sample and an individual level. We find wide variation in implicit discount rates for fatality risk between individuals, as well as between-individual heterogeneity in discounting functional forms. In aggregate, the sample is best characterised by subadditive discounting. Our work has implications for the academic investigation of intertemporal choice involving mortality risks, and potentially for the evaluation of policy options with delayed mortality risk outcomes. A thought experiment cautions against the standard practice of assuming that exponential discounting characterises society's time preferences.

Keywords: Discounting; Time preference; VSL; Latency; Mortality risk; Valuation; Resource allocation.

Acknowledgements: This article and the work it describes were funded by the Health and Safety Executive (HSE). The article's contents, including any opinions and/or conclusions expressed, are those of the authors alone and do not necessarily reflect HSE policy. The paper was also supported by the Leverhulme Trust [grant number RP2012-V-022].

1. Introduction

When an outcome is delayed, it tends to matter less to us. This is the concept of time discounting, which has held a descriptive and normative place in economics at least since Irving Fisher's *Theory of Interest* (1930). The two key components of a basic time discounting framework are the discount rate, which captures how the importance of an outcome changes with delay; and the functional form through which this discount rate is expressed. The empirical investigation of time discounting predominantly (though not exclusively) focuses on trade-offs between small money payoffs sooner and larger ones later. However, practical applications can be found in all aspects of life where time matters, from individual financial decision-making to inter-generational environmental trade-offs.

This paper explores time discounting for fatality risks. Our specific setting is the Value of Statistical Life (VSL) applicable to delayed – i.e. latent - cancer fatalities. Stated preference estimates of the VSL are well-established (Viscusi and Aldy, 2003) and have been widely accepted in policy cost benefit analyses (e.g. Department of Transport, 1988; Office of Management and Budget, 1996). However, there is no consensus in the literature about how the VSL should be discounted when the prevented fatalities would have occurred after a delay, or latency period. This context matters because the rate at which society chooses to trade off resources today for safety in the future has immediate practical implications for resource allocation, as well as far-reaching consequences for fatality risks in the future.

Though this topic has received some interest in the academic literature (as we will outline below), many academic and policy applications have made two simplifying assumptions: that discounting can be captured by a single parameter applied for all individuals; and that discounting is best described by an exponential function. We challenge both of these assumptions empirically, and demonstrate in the Discussion that their continued imposition

may result in estimates of discount rates, and ultimately in societal resource allocations, that do not accurately reflect society's preferences¹.

1.1 Discount rates for the VSL

Most studies investigating the VSL for delayed risks simply assume a value for the discount rate, typically between 3% and 5% per annum (Gayer, 2002; Davis, 2004; Adamowicz et al, 2011; Cameron et al, 2009; Cameron and Deschazo, 2013). Other studies derive a discount rate from their data, calculating the relative weight of present and future outcomes implied by their subjects' choices. In these studies, the elicited discount rates range from zero, implying no additional weight is placed on the present compared to the future (Hammitt & Haninger, 2010; Alberini & Ščasný, 2011, 2013) to 22% (Lazaro et al., 2001). Most estimates in the health and physical risk literature are between 1.5 and 11% (Viscusi & Moore, 1989; Horowitz & Carson, 1990; Ganiats et al, 2000; Hammitt & Liu, 2004; Alberini et al. 2006, McDonald et al, 2016).

These elicited discount rates are 'effective discount rates', which differ from pure time preference rates because they capture pure time preference (if any) plus any other co-varying effects of delay. (For example, delaying an outcome increases uncertainty about whether it will eventually be experienced.) Nonetheless, any empirically elicited discount rate, in any context, can only ever be 'effective', since pure time preference rates cannot be observed directly.

A shared assumption amongst all of the studies referred to above is that the functional form of time discounting is exponential, implying time consistency². This assumption is often

¹ Theoretical implications of discounting in policy evaluations are outlined in Cropper & Portney (1990), Krahn & Gafni (1993) and Johannesson et al. (1994). Under some circumstances, the Social Time Preference Rate (STPR) underpinning public policy ought to respect individual's private time preference rates (Krahn and Gafni, 1993; Jones-Lee et al, 2015).

necessary due to the design of the studies, with little variation in the delay until the later outcome. To date, no existing study directly and specifically tests the exponential, hyperbolic and sub-additive (see Section 1.3) functional form hypotheses in the discounting of one's own future fatality risks, and none identifies the discounting functional forms for fatality risks that are appropriate for individual participants. Our work addresses these shortcomings in the literature. In designing this study, we drew on previous studies that investigated discounting functional forms for non-market outcomes in other, related, contexts. In what follows, we briefly outline this literature.

1.2 Discounting functional forms for non-market outcomes

Non-exponential discounting models dominate the literature in experimental economics and psychology. Frederick et al. (2002) review these contributions, referencing financial, health and other contexts³. Non-exponential discounting has since been explored in the non-market valuation literature in the contexts of the environment, health and, though less often, lives lost or saved.

Environmental discounting studies are inconclusive about which discounting functions are the most descriptively accurate. Both Viscusi et al (2008) and Richards and Green (2015) found evidence compatible with hyperbolic or quasi-hyperbolic discounting (Phelps and Pollack, 1968; Elster, 1979; Laibson, 1997). In contrast, Meyer (2013b) demonstrated that water clean-up valuation data could be better accommodated by an

² The exponential discounting assumption is also made in policymaking for short term delays: in the UK, health and safety outcomes are discounted at the constant Social Time Preference Rate of 1.5% per annum (HSE, 2007); and in the US, the Social Rate of Time Preference is 3%, although the OMB states that health outcomes could be seen as an exceptional case for discounting purposes (OMB, 2003). However, declining discount rate schedules are advised for delays of over 30 years in the UK (HM Treasury, 2013) and in France. See Cropper et al (2014) for a brief review.

³ Although see Ahlbrecht and Weber (1997) and Andersen et al (2014) for evidence against the hyperbolic discounting model.

1 exponential than a hyperbolic specification. Despite this, Meyer (2013a) used data from
2 Meyer (2013b) to show that the present value of future water clean-up is similar under each
3 discounting model.

4 In contrast to the environmental literature, there is considerable agreement that non-
5 exponential discounting characterises time preferences for non-fatal health states (Chapman
6 and Elstein, 1995; Bleichrodt and Johannesson, 2001; Van der Pol and Cairns, 2001; 2001;
7 2011). Given this, one might assume that the same holds for fatal outcomes. However,
8 individuals sometimes prefer to experience poor health states sooner rather than later (e.g.
9 van der Pol and Cairns, 2002)⁴. The role of time preference is unclear under such
10 circumstances. In contrast, since fatality risks are unlikely to be preferred sooner to later
11 (although see Nielsen et al, 2010 and Hammitt and Tunçel, 2015), these risks are more
12 analytically straightforward for eliciting information about time preferences, and it is likely
13 that different effective discount rates and functions will apply.

14 Non-exponential discounting has been explored for changes in expected *numbers* of
15 fatalities prevented. Examples include Cropper et al. (1992), reanalysed in Henderson and
16 Bateman (1995) with reference to the implications of real policy decisions; Cairns and Van
17 der Pol (1997a), Cairns and Van Der Pol (1997b), and Alberini et al. (2009), all of whom find
18 support for non-constant discounting of lives saved. However, these studies elicit preferences
19 over different *numbers* of fatalities, and so do not reveal private time preference rates for
20 one's own future fatality risks. They do not provide directly relevant evidence about the
21 appropriate rate for discounting the VSL.

⁴ Where health states are temporary, this can be explained by models in which utility changes over time, as well as by anticipation and dread effects (Loewenstein and Prelec, 1993), and the belief that illnesses occurring at different times will impact differently on one's life.

A small number of papers do provide insight into preferences regarding the timing of one's own future fatality risks. Revealed preference evidence is provided by Viscusi and Moore (1989) and by Scharff and Viscusi (2011), but neither study explored the functional form of discounting. The only study that has examined functional forms for the private discounting of own future fatality risks is Rheinberger (2011) who elicited discount rates through a choice experiment in the context of alpine natural disasters. Rheinberger rejects the hyperbolic functional form in favour of the exponential functional form, which is surprising given the weight of evidence in other contexts that rejects exponential discounting. However, Rheinberger did not set out with the sole aim of testing discounting functional forms, and so to date there has been no study specifically dedicated to this objective.

The survey reported in this paper addresses this gap: it was designed to allow the elicitation of discount rates from Risk-Risk survey data, and can be analysed at the level of the individual. Discount rates are inferred from choices between increases in fatality risks from two causes (road accidents and cancer) occurring at different times in the future. The delays were varied to reveal rates of discounting and also to distinguish between three competing hypotheses about the functional form (exponential, hyperbolic, and subadditive).

1.3 Eliciting discounting from Risk-Risk survey data

We elicited discount rates from pairs of Risk-Risk relativities. These relativities represent the utility loss from fatality by cancer relative to the utility loss from fatality in a road accident (Van Houtven et al, 2008, McDonald et al, 2016).

Our method employs the structural relationship developed and validated in McDonald et al (2016). The ratio of utility loss from fatality by cancer at time t and from fatality in a road accident at the same time t is assumed to be constant so $C_t = R_t(1 + x)$, where C_t is the VSL for risks of fatality from cancer at time t , R_t is the VSL for risks of fatality in a road accident

at time t and $(1+x)$ is the context premium for cancer relative to road accidents. We assume that any fatality risk is discounted according to some function (as yet unspecified) which we capture via a discount factor θ_τ (the proportion of the outcome's value retained when it is delayed by time τ).

Hence, for cancer at time T and a road accident at time t :

$$C_T = \theta_T C_0 = \theta_T R_0(1+x)$$

$$R_t = \theta_t R_0.$$

It therefore follows that the relativity between C_T and R_t , which we denote by $C_T R_t$, is given by:

$$C_T R_t = (1+x) \frac{\theta_T}{\theta_t}$$

When we take the ratio between two relativities that differ in the timing of the cancer and road accident fatalities, the context premium cancels allowing us to elicit the relative size of the discount factors in each case without needing to know the context premium.

$$\frac{C_T R_t}{C_{T'} R_{t'}} = \frac{\theta_T}{\theta_t} \frac{\theta_{t'}}{\theta_{T'}} \quad (1)$$

We will use the convention that ϕ refers to the ratio on the left hand side of equation (1). Equation (1) will take different forms according to the discounting functional form assumed.

Exponential

If discounting is exponential (Samuelson, 1937), the discount factor takes the form $\frac{1}{e^{\delta\tau}}$ where δ represents the discount rate (per period). Exponential discounting is characterised by a constant and unchanging discount rate over the discounting horizon.

$$C_T R_t = \frac{(1+x)}{e^{\delta(T-t)}}$$

$$\phi = e^{\delta[(T'-t')-(T-t)]}$$

This is an equation in one unknown (δ) and can be solved analytically for δ .

Hyperbolic

To account for empirical evidence that the discount rate (when elicited under the assumption of exponential discounting) declines with delay from the present until the outcome is realised (Ainslie & Herrnstein, 1981; Thaler, 1981), the hyperbolic discounting framework was developed⁵. A range of hyperbolic discounting specifications have been proposed, and a useful review can be found in Andersen et al (2014). Here, the discount factor takes the general form $\frac{1}{(1+\delta\tau)^{\gamma/\delta}}$, where δ is the discount rate, τ is the delay until the outcome and γ captures the extent to which the function differs from constant discounting (see Loewenstein and Prelec (1992) for an explanation of the role of γ in shaping the generalised hyperbolic discounting function). This simplifies (assuming $\gamma = \delta$) to $\frac{1}{(1+\delta\tau)}$.

In this framework,

$$C_T R_t = (1 + x) \left(\frac{(1+\delta t)}{(1+\delta T)} \right)$$

$$\varphi = \left(\frac{(1+\delta t)}{(1+\delta T)} \right) \left(\frac{(1+\delta T')}{(1+\delta t')} \right)$$

Again, this is an equation in one unknown (δ) and its algebraic solution is provided in Appendix 1.

Subadditive

The subadditive discounting model (Read, 2001; Scholten & Read, 2006; Rambaud & Torrecillas, 2010), assumes that the interval between the times being considered, as opposed to the delay until these outcomes, generates the decline in the discount rate. The per-period

⁵ The quasi-hyperbolic (“beta-delta”) model (Phelps and Pollack, 1968; Elster, 1979; Laibson, 1997) also allows for additional weight to be placed on the current period, but the rest of the time horizon is characterised by exponential discounting. We omit this case because to test it empirically requires an immediate outcome to be available, which we felt would not be captured by even the shortest time scale that can be communicated in our study relating to fatality risks (“during the coming year”).

discount rate implied by choices over a long interval is *lower* than the per-period discount rate implied by choices over the same period if broken down into shorter intervals. As such, the discounting fraction can be expressed as $\delta^{(\hat{\tau}-\tau)^s}$, where $\hat{\tau}$ and τ are the later and earlier time intervals under consideration, δ is the underlying discount rate, and s captures the non-linear perception of time whereby individuals overestimate short intervals and underestimate long intervals of time (Read, 2001). In this case we have:

$$C_T R_t = (1 + x) \delta^{(T-t)^s}$$

where s is a parameter, typically between 0 and 1, which captures non-linearity of preferences over time.

$$\varphi = \left(\frac{\delta^{(T-t)^s}}{\delta^{(T'-t')^s}} \right) = \delta^{[(T-t)^s - (T'-t')^s]} .$$

This is an equation in a single unknown (given the usual assumption that $s = 0.5$) and can be solved algebraically.

In the design of most intertemporal choice studies, the influence of delay until an outcome (which underpins hyperbolic discounting) is confounded with the interval between the time of the two outcomes in the choice. For example, a study might elicit three WTP amounts: WTP for an outcome today, WTP for an outcome 10 years from now, and WTP for an outcome 20 years from now. Discount rates can be calculated by comparing WTP today with WTP in 10 years, and also by comparing WTP today with WTP in 20 years. If the discount rate from the former comparison is greater than that from the latter, researchers would typically conclude that it declines with the *delay*, and so supports hyperbolic discounting. However, an equally valid interpretation is that the discount rate declines with the *interval* between the sooner and later fatalities in each comparison (the interval is 10 years in the first comparison and 20 years in the second).

Read and Roelofsma (2003) state:

“Studies that confound delay and interval will invariably obtain values of δ that increase with delay, yet this relationship will be augmented, if not created, by the confounding of delay and interval. Future experiments into time discounting must take care to avoid this confound.” (Read and Roelofsma, 2003)

Our study is designed so as to allow these hypotheses to be disentangled, which distinguishes it from previous explorations of intertemporal choice for non-market outcomes.

2. Survey Methods

2.1 Survey design

The survey is intended to distinguish between individuals’ discounting behaviour in two dimensions. The first is the (effective) discount rate, which is the rate of time preference that characterises an individual, given a specific discounting function. The second is the discounting function itself. The survey was designed to allow the exponential, hyperbolic and subadditive discounting functions to be distinguished. As stated in section 1.3, under exponential discounting neither the interval nor the average delay influences the elicited discount rate. In contrast, under the assumption of subadditive discounting, the discount rate declines with the interval; and under the assumption of hyperbolic discounting, it declines with delay. Our survey allows us to distinguish between these cases by incorporating a range of different intervals (the time between the road accident and the cancer fatality, $T - t$) and delays (the average time between the present and the cancer and road accident fatalities, $(T + t)/2$).

Piloting suggested that respondents could provide a maximum of ten relativities before becoming fatigued. As such, the survey elicits ten $C_T R_t$ relativities, outlined in Table 1 along with their timing characteristics.

[Table 1 about here]

2.2 Relativities elicitation procedure

In our approach, discount rates are calculated from relativities between fatalities at different times. These relativities were elicited using a risk-risk trade-off method (Viscusi et al., 1991) in which the respondent expressed the size of a risk increase in one cause that made them indifferent between it and a fixed risk increase in another cause. This tells us the relative size of the utility loss for the two causes, as demonstrated in Van Houtven et al (2008). In this way, it is theoretically equivalent to eliciting two separate Willingness-to-Pay based VSLs, one for each cause, and taking the ratio. The Risk-Risk method has been argued to be easier for participants since it avoids the need to trade-off potentially incommensurate attributes i.e. risk and money (Magat et al, 1996).

To establish the Risk-Risk relativity, the respondent was first asked whether they would prefer to take a 50 in 60 million increase in their risk of cancer fatality at time T or in the risk of road accident fatality at time t ($t < T$)⁶. They were told that the baseline risk in each case was 1000 in 60 million⁷. Figure 1 gives an example of this question. Respondents could choose one of the fatality risks by circling the relevant option on their answer sheet, or indicate indifference by drawing an equality sign between the two options. If indifference was indicated, no choice list table would be necessary and the relativity would be recorded as 1:1.

[Figure 1 about here]

⁶ We used two types of fatality in each comparison instead of one to avoid excessive emphasis on timing that could result in exaggerated estimates of time preferences (see the evidence on cross-modal versus uni-modal discounting in Cubitt et al (forthcoming), the focusing illusion (e.g. Kahneman et al , 2006) and related findings in McDonald et al (2016).

⁷ At the time of the study, the population of the UK was around 60 million and the number of road accident fatalities (for driver or passengers) was close to 1000 per year. The same baseline was used for cancer (referred to as “a group of cancers” with the characteristics relevant for each question), because initial piloting suggested that baseline effects were so strong that any influence of context or timing was impossible to observe.

If the respondent did not express indifference, they then filled in a choice list table tailored to their original choice. In each row, the fatality risk that they had *not* chosen to increase was fixed at 50 in 60 million (column D in Figure 2). The fatality risk that they had chosen was increased incrementally (Column C). Thus the respondent faced a trade-off between a smaller risk increase in a more feared cause of death against a larger risk increase in a less feared cause of death. The row in which the respondent switched to choosing the 50 in 60 million increase in the ‘worse’ cause indicates bounds on the risk that would make them indifferent, indicating the relativity $C_T R_t$, which was the basis for the calculation of discount rates. An example of the multiple list table is provided in Figure 2.⁸

[Figure 2 about here]

2.3 Preliminary and supplementary questions

Prior to the ten questions outlined in Table 1, respondents completed a learning session which lasted approximately 45 minutes. First, we explained the meaning of risk as “the chance that something bad happens”, and introduced the concepts of baseline risk and risk increases. Next, we introduced respondents to the concept of delay, inviting them to consider how delaying a risk changed how they felt about it. We introduced the Risk-Risk response mechanisms using the contexts of influenza and domestic fires, allowing participants to practice filling in an elicitation table for these fatality contexts. These risks had different baselines, and the numbers in the table were different from those in the main questions, to minimise the chance of anchoring on the values in the practice session. We then explained what we meant by cancer and road accident fatalities, stating that the cancer would be preceded by one year of illness, with symptoms that worsen until death at time T , while

⁸ The results of the choice list table were shown through various validity tests to be robust to common criticisms including midpoint bias and refusal to switch. See McDonald (2013), section 4.9 for details.

the road accident fatality would be as a driver or passenger, and there would be no long period of suffering preceding fatality. We stressed that the cancers were not caused by the respondent's behaviour (e.g. smoking) but instead were due to exposure to environmental or workplace carcinogens. This was to establish no obvious reason for the respondent to assume that their baseline risk differed substantially from that of the average person. We elicited from each respondent their perceived risk of fatality in road accidents, compared to the average person.

After the learning session, respondents completed the ten questions described above, and then provided demographic information.

2.4 Implementation

The sample size was 112. All respondents were undergraduate or postgraduate students at Newcastle University, recruited as a convenience sample from one age cohort of the general population. The survey was administered in groups during February and March 2012. While there was a moderator and assistant on hand in all groups to answer clarification questions, all relativities were elicited on an individual basis and conferring and discussion within the group were not allowed. We tested the elicited relativities for sensitivity to the groups that respondents were in and can reject significant group effects in all cases. Because we used fatality risks as the object of the study, the survey responses could not be incentivised, but respondents received a show-up fee of £20. Sessions lasted 1 hour and 45 minutes on average.

The demographic characteristics of the sample are provided in Table 2.

[Table 2 about here]

3. Results

3.1 Overview

As discussed, the discount rate is elicited from pairs of relativities, each of which contains information about the relative severity of the two different causes of fatality given the delay until they would occur. Therefore, each elicited rate is underpinned by four ‘fatality – timing’ outcomes. The underlying timings are the key to unlocking the most appropriate discounting assumption, because the discounting functional forms can be distinguished by the dependence of the elicited discount rate upon the delay and interval of the timings underpinning their elicitation. The analysis of the elicited discount rates comprises three parts, each relating to a different degree of individual-specificity. The first is aggregate analysis based on discount rates derived from the sample central tendencies; the second is aggregate analysis, but based on individual level discount rate data; and the final part is the analysis of individual-specific discount functions derived for each respondent based on their own responses.

3.2 Aggregate discounting analysis using sample average relativities.

Table 3 shows the central tendency results for each of the ten relativities. The geometric mean is presented alongside information about the latency interval and the average delay that characterise the comparison underpinning the relativities. We use the geometric mean of the relativities because the data are ratios. Observations that imply a $C_T R_t$ relativity greater than or equal to 60,000:1 are excluded⁹.

The geometric means demonstrate that when the road accident is much sooner than the cancer, the road accident is deemed worse with the $C_T R_t$ relativity below 1 (for example

⁹ Respondents stating a risk increase of 30 million in 60 million or higher to avoid a 1 in 1,200,000 increase in their risk of the other fatality (implying willingness to accept a 50:50 chance of death by their chosen cause) are excluded. Protest responses, where participants claimed they “would never switch” are also excluded. The number of affected responses is outlined in Table 3.

question 3 where the timings are 2 and 25 years). When the fatalities are closer in time (for example question 4 where the timings are 2 and 5 years) the preference for avoiding cancer is strong enough that the relativity is above 1. In question 10, when both fatalities would occur at the same time, the relativity is significantly greater than 1. These patterns validate the quality of the data, support the notion of a context effect offset by discounting, and provide support for the discounting elicitation procedure described above.

One apparent anomaly is the decline in relativity from the $C_{10}R_1$ case to the $C_{10}R_2$ case, when our model would predict an increase. However, these relativities are not statistically significantly different, which suggests that the difference between 1 year and 2 years from the present seemed negligible to respondents in the comparison with cancer 10 years from now. Furthermore, there is some evidence from a free-text entry box to explain why some respondents selected a lower risk in the $C_{10}R_2$ question than the $C_{10}R_1$ question, reflecting an expectation that their baseline road accident risk might rise. For example: “*Not in cars much but will be yr [sic] after next*” and “*expect to be driving more in 1y [sic] as have a job*”.

[Table 3 about here]

As explained in section 1.3, discount rates (δ) can be elicited from pairs of questions. Combining the ten questions’ average (geometric mean) relativities in this way generates 43 estimates of the exponential discount rate for the sample (see Figure 3). All 43 rates¹⁰ are presented in the matrix in Figure 3.

[Figure 3 about here]

The mean of the discount rates presented in the matrix is 11.0% (s.d. 9.15%) and the median is 10.1%. The discount rates are within sensible bounds in comparison to the

¹⁰ The empty cells are where $T - t = 0$ so no discount rate can be calculated.

literature. The elicited rates are all positive except where Q1 and Q2 are combined, which is due to the lower relativity in Q2 than in Q1 discussed above.

To distinguish between the exponential, subadditive and hyperbolic discounting functions, we explore how the elicited discount rates vary with the intervals and delays that characterise the relativities that underpin them. Figures 4a and 4b are non-parametric plots of the sample average discount rates as a function of the delay and of the interval, created in STATA using the *Lowess* (locally weighted scatterplot smoother) command with bandwidth set to 0.3.¹¹ Each discount rate is inferred from a pair of relativities, so each smoothed discount rate is plotted against the mean of the two delays, or the two intervals, that characterise its underpinning relativities. The plots reveal a declining pattern of discount rates with respect to both delay and interval, which suggests that non-standard discounting is likely to characterise the majority of the sample. The declining function is largely monotonic for the interval but not for the average delay, which suggests that subadditive discounting might be more appropriate than hyperbolic discounting in characterising the sample as a whole.

[Figures 4a-4b about here]

5.3 Sample level analysis based on individual level discount rates

We have generated preliminary evidence in favour of subadditive discounting to describe the sample in aggregate. However, the analysis so far rests on just 43 discount rates (in Figure 3), reflecting the level of detail available on the sample level. To improve upon this, we elicit the discount rates in the same way as we did for the sample, but we do this on an individual level resulting in up to 43 discount rates per respondent¹². This generates 4336 elicited discount rates, with a mean of 12.2% per annum and median of 6.4% per annum. This

¹¹ Choosing the 0.3 bandwidth allows the patterns to be seen in greater detail than the 0.8 default level. However, the versions based on 0.8 are available on request.

¹² For some individuals there are fewer because they failed to provide one or more of the relativities.

sample size provides enough explanatory power to perform fixed effects regression analysis of the elicited discount rates against the interval and delay, allowing the statistical significance of the latency and delay effects to be explored. We use fixed effects regression to control for individuals' unobservable differences, since the underlying relativities are not independently generated. Robust standard errors are reported. The results are presented in Table 4.

[Table 4 about here]

Models (1)-(3) generate estimates of the relationship between the discount rate and the latency intervals and delay. Model (1) relates the discount rates to the latency interval, whose coefficient is negative and significant ($p < 0.001$). This means that where the outcomes are temporally further apart, the discount rate is lower than when the outcomes are closer together. This supports the hypothesis of subadditive discounting. Model (2) uses delay to explain the discount rate and again the coefficient on the timing variable is negative and significant. The longer the average delay until the outcomes, the lower the implied discount rate. This supports the hypothesis of hyperbolic discounting but is also compatible with the subadditive discounting hypothesis. As such, models (1) and (2) are insufficient to fully distinguish between the hyperbolic and subadditive hypotheses. They do, however, support the conclusion that exponential discounting does not describe the sample as a whole.

Model (3) is introduced to distinguish between subadditive and hyperbolic discounting. In model (2) the delay parameter might act as a proxy for the interval. To address this, in model (3) both delay and interval are included. The coefficients capture the effect of each timing variable controlling for the other. In model (3), the significance of the latency interval is maintained and the coefficient appears to be stable. However, delay is

insignificant ($p > 0.1$). This is evidence that subadditive, as opposed to hyperbolic discounting appears to best characterise the sample as a whole.

3.4 Individual level analysis based on individual discount rates.

The analysis so far, based on the sample in aggregate, has allowed us to explore the discounting hypotheses with robust statistical tests. This section builds upon the previous analysis by providing preliminary evidence regarding the most appropriate discounting assumption for each individual within the sample. The analysis rests on a maximum within-person sample size of 43, so the results should be treated as exploratory, but they provide some insight into the heterogeneity of discounting functions between individuals. We use the same principles as for the aggregate sample, including OLS regression on latency intervals and average delays, but this time a separate regression is run for each individual respondent. For each of the 112 individuals, regression is run of their elicited discount rates (up to 43 per person) against the average delay and the latency interval characterising the relativities underpinning them, and the sign and significance of the coefficients on these parameters are used to classify the respondents into discounting “types”.

If neither the average delay nor the latency interval is significant, we cannot reject the hypothesis that the individual is an exponential discounter (alternatively their answers might display randomness, but they preclude hyperbolic or subadditive discounting). Every other respondent is characterised by nonstandard discounting functional forms. Within this group, subadditive discounters show decreasing discount rates with the interval between the outcomes considered, while hyperbolic discounters show decreasing discount rates with delay. The two classifications can co-exist, because a respondent could have negative and significant coefficients on the delay and the interval and would be classified as displaying hyperbolic-based subadditive discounting. It is conceivable that discount rates could

significantly increase with the delay or with the interval, but this would contradict most theoretical accounts of discounting behaviour. The definitions and proportions of each classification are summarised in Table 5.

[Table 5 about here]

The majority of respondents (n=92) successfully responded to all ten relativity questions, generating 43 discount rate estimates for regression. For 12 individuals the number of elicited discount rate estimates is between 14 and 34. Eight individuals were excluded from the analysis because they answered fewer than half of the questions resulting in a sample size of 10 or below for regression. The remaining sample is 104.

Of these 104, for 36 respondents neither delay nor interval is significant in explaining their discount rates, so we cannot reject the hypothesis that they are exponential discounters. Probit analysis, not reported here, found no evidence that demographic characteristics predict whether an individual is best characterised by non-standard discounting. The modal classification of respondents (41%) classify as subadditive. Hyperbolic classifications comprise just 15% of the full sample. Two individuals had negative and significant coefficients on both timing variables, and so were characterised by a hyperbolic-based subadditive discount function. 9% of the sample had positive coefficients on delay and/or interval and were therefore unclassified.

It is possible that some respondents answer randomly. To explore the impact this would have on the elicited discount rates, we generated sixty sets of random values for the ten relativities, and then used these to infer sixty sets of 43 randomly generated discount rates. We analysed these in the same way as for the real responses. First, we ran fixed effects regressions and found that neither delay nor interval were significant in explaining the elicited (randomly-based) discount rates. We then analysed the discount rates elicited from

each (hypothetical) individual, running regressions on the level of the individual. Of our 60 hypothetical respondents, 47 would be classified as exponential, 8 as hyperbolic and just 5 as subadditive. This means that, if any respondents were answering randomly, then the true proportion of exponential discounters in our sample is likely to be even lower than our identified 34 per cent.

Since we find that the sample in aggregate appears best described by a subadditive discounting assumption, we re-calculate the discount rates on the sample aggregate basis (as in Figure 3) under the assumption of subadditive discounting. Appendix 1 shows the procedure used for this calculation. The resulting discount rates, calculated on the sample level are provided in Figure 3'. A summary of the individual-level discount rates (up to 43 per person) calculated under subadditive discounting, as well as under exponential and hyperbolic, is also provided in Appendix 1.

[Figure 3' about here]

4. Discussion

This study addresses an underexplored question in the valuation of health and fatality risks: what form does private time discounting take when the future outcomes are changes in individuals' own fatality risks? We convert Risk-Risk relativities into discount rates using simple algebraic manipulation, and test the resulting discount rate estimates for sensitivity to the interval between the sooner and later outcomes, as well as to the average delay until the outcomes would occur. This allows us to distinguish between the different discounting functions that best characterise discounting behaviour in the domain of health and physical risk. Our work (i) demonstrates non-exponential discounting in a new context (private discounting of own future fatality risks) that is relevant for real-world policy decisions; (ii) allows us to analyse discounting functional forms at an individual level, demonstrating the

heterogeneity in discounting functional forms for fatality risks within the population; and (iii) allows a direct test of sub-additive (as opposed to hyperbolic) discounting, which to our knowledge has not previously been tested for directly in any of the non-market valuation literatures.

We find wide variation in estimated discount rates across respondents. This suggests the practice of eliciting a single aggregate discount rate for the sample- or imposing a given discount rate- is a simplification which could seriously impair the validity of the elicited valuations of latent outcomes.

Perhaps more significantly, since just one third of respondents in this study can be best characterised by the exponential discounting assumption, this evidence leads us to doubt the descriptive validity of the standard assumption of exponential discounting typically used in academic valuations as well as in policy applications. The majority of respondents are instead characterised by non-standard discounting functions. The evidence in this study favours the subadditive discounting function, which appears to characterise 41 per cent of respondents when analysed at the level of the individual. In contrast, hyperbolic discounting functions perform best for just 15 per cent of the sample. We find that the negative relationship between the discount rate and the delay until the outcome is not robust, and show that the ‘delay effect’ is likely to be capturing the more fundamental effect of the interval. The subadditive discounting function is also favoured when the sample is analysed in aggregate, with the subadditive function being the most appropriate when the discount rates are derived from sample average data.

The study is not without limitations. First, we sampled young adults, and so the elicited discount rates and associated functional forms cannot necessarily be generalised to the population as a whole. Nevertheless, we would argue that this does not render the results

uninformative since our employment of a convenience sample is analogous to the use of such samples in experimental economics for the purpose of theory falsification (Davis & Holt, 1993 p. 32) whereby a violation of theory by any particular group is enough to cast doubt on the validity of the theory in general. In our case, the theoretical assumption is the applicability of an exponential discounting functional form, which is clearly violated by a large proportion of our sample.

In addition, although we acknowledge the critique, raised for example in Andersen et al (2014), that “it is difficult to make inferences about behavior in general from a small student population”, for the three questions in our study that directly replicate questions asked of 30 to 50 year olds in McDonald et al (2016), no meaningful differences were found between the relativities elicited in that study, and those elicited here¹³. Another complication, more specific to our setting, that arises from sampling young adults is that their risks of developing cancer in the medium term are low. Nonetheless, we found that respondents tended not to reject the scenarios we presented to them, and the patterns of their responses demonstrate the anticipated trends, with relativities that tended to increase with the delay until the road accident and decrease with the delay until cancer.

The second limitation is our assumption that the context premium (x) is constant over time. That is, we assumed that the relative magnitudes of the VSL for cancer and road accidents holding time constant is the same no matter when the fatalities would occur. While the relative size of these VSLs could conceivably differ at different points in time, this assumption does not affect the conclusions about the heterogeneity in functional forms of

¹³ Geometric means with 95% confidence intervals for the relativities from the 30-50 year old sample in McDonald et al (2016) for $C_{10}R_1$, $C_{10}R_2$ and $C_{25}R_2$ (respectively) are: 1.12 [0.58, 2.16]; 0.81 [0.40, 1.64]; 0.28 [0.14, 0.57]. Corresponding statistics from the young adults surveyed here are 0.97[0.59, 1.60]; 0.72 [0.42, 1.23]; 0.35 [0.21, 0.59]. Though not identical, these are remarkably similar and not statistically distinguishable.

discounting, unless the context premium varies significantly and systematically between relativities *as a function of* the interval between the fatalities or the average delay. An initial empirical test (McDonald et al, 2016) provides evidence in favour of a constant context premium, but a more detailed investigation would be a beneficial next step.

These limitations aside, this study could be interpreted as showing that the standard exponential discounting assumption used in the majority of academic and policy valuations of future risks to life and health is questionable, since it may not accurately reflect the reality of choices over fatality risk outcomes over time. Using the data generated in this study, we set up a ‘thought experiment’ to enable us to estimate the level of distortion this might introduce to the VSL for delayed fatality risks in typical policy scenarios. This distortion turns out to be substantial. The thought experiment involves specifying what the implications are for the size of the VSL when choosing between using the standard exponential discounting assumption and the subadditive discounting assumption that best characterises this sample, for different lengths of delay.

3.1 Thought experiment: Implications for the VSL

Suppose for illustration that the discount rate, elicited under the assumption of exponential discounting, is set at the level derived from this study, 12.2%. A policymaker would then multiply the standard VSL value by a discount factor of $\frac{1}{e^{0.122 \cdot T}}$ where T is the delay until the fatality risk. If the individuals were using a subadditive discounting function instead, then the appropriate VSLs for delayed fatality risks are very different from those calculated using the exponential form. To demonstrate this, we re-elicited discount rates under the exponential-based subadditive discounting assumption¹⁴ and re-constructed the discount

¹⁴ Proposed in Read (2001). Details about eliciting subadditive discount rates are provided in Appendix 1.

factors for a latent outcome at different times, relative to an outcome at the present time. The result of this is shown in Table 6, where the average (geometric mean and median) of all individuals' elicited discount rates is used to reconstruct the discount factors.

[Table 6 about here]

This, applied to a VSL of £1.6 million, generates very different estimates of the present value of a statistical fatality prevented 60 years from the present. The functions using the geometric means of the exponential and subadditive discount rates are plotted in Figure 5. All four approaches show that as time passes, the discounted value of a statistical life worth £1.6 million today decreases. However, there is a much steeper decline in the subadditive case than in the exponential up to 35 years' delay, with the exponential discounting assumption overstates the present value of the VSL. At this time, the functions cross and thereafter the exponential assumption understates the present value of the VSL.

[Figure 5 about here]

As such, the implications for the allocation of resources to risk-reducing policies with outcomes that differ in their timing will be sensitive to the choice of discounting function used, particularly in the medium term. For a five year delay, the discrepancy in the present value for the VSL is calculated as £0.49 million, with the discounted VSL in the exponential case more than double that calculated under the assumption of subadditive discounting. The discrepancy falls to £0.18 million for the 25 year delay, and by the 40 year delay, the subadditive estimate is £19,521 larger than the exponential. If our results generalise to the wider population, then the imposition of the exponential discounting assumption where the subadditive approach is more appropriate will distort the values input to policy and hence potentially result in sub-optimal resource allocation, provided that the main objective of welfare-maximisation in policy is to respect the preferences of individuals.

4. Concluding comments

The study and thought experiment reported in this paper provide evidence against the standard approach in policy and academic applications of imposing a single, exponential discount rate in the calculation of the present value of fatality risk reductions. In practice, however, the lessons learned from this study for the policy valuation of latent outcomes are challenging to apply. When calculating the present value of a latent outcome, current practice is to value the future outcome and apply a standardised discount rate. In the light of this study, the imposition of such a rate may overweight medium-term and underweight long-term outcomes relative to outcomes now. However, it is not straightforward to prescribe a better course of action. The normative aspects of exponential discounting make it attractive, because of the time-consistency of valuations- and hence of policy decisions. Nonetheless, we hope this study provokes a conscious debate about how to prioritise the intertemporal consistency offered by the exponential discounting assumption against the respect for public preferences provided when taking non-standard discounting into account.

Regardless of the policy consequences, the authors are persuaded that academic research to elicit valuations of latent outcomes in any domain would be improved by a thorough exploration of the discounting behaviours underpinning these valuations. Rather than a dedicated ‘one-off study’, this aim may be better served by a small change in survey design in future stated preference valuation surveys to facilitate elicitation of discount rates as a matter of course within the main body of the survey. The present study shows that this is possible, and in fact quite easy. As the body of data grows we can establish a set of broad principles regarding the nature of time preferences in mortality risk valuation.

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8

Figures

Figure 1: Initial response sheet

INITIALS _____
DATE _____

RR AS

QUESTION 2

Your current risk of dying by each cause is **1000 in 60 million**.
Which would you choose, if you had to:

C	D
An increase in my risk of dying in a car accident during the year after next (2014) of 50 in 60 million	An increase in my risk of dying from cancer 10 years from now of 50 in 60 million

BEFORE ACCIDENT

NOW → Year after next

TIME

NO SYMPTOMS SYMPTOMS

NOW → 9th year → 10th year

TIME

CIRCLE THE ONE YOU WOULD CHOOSE

- 1 **Figure 2:** Multiple list table for a respondent that originally chose the increase in road
- 2 accident risk

INITIALS _____
DATE _____

RR AS

ANSWER SHEET 2A

C <i>Dying in a car accident during the year after next 1000 in 60 million</i> RISK INCREASE :	OR	D <i>Dying from cancer 10 years from now 1000 in 60 million</i> RISK INCREASE :	
50 in 60 million	OR	50 in 60 million	<i>C</i>
100 in 60 million	OR	50 in 60 million	
140 in 60 million	OR	50 in 60 million	
180 in 60 million	OR	50 in 60 million	
220 in 60 million	OR	50 in 60 million	
260 in 60 million	OR	50 in 60 million	
300 in 60 million	OR	50 in 60 million	
340 in 60 million	OR	50 in 60 million	
380 in 60 million	OR	50 in 60 million	
420 in 60 million	OR	50 in 60 million	
	OR	50 in 60 million	<i>D</i>

3

4

- 1 **Figure 3:** Matrix of elicited effective discount rates- sample level (exponential assumption),
 2 calculated using equations (3) and (4).

Cause A	C ₁₀ R ₁	C ₁₀ R ₂	C ₂₅ R ₂	C ₅ R ₂	C ₇ R ₂	C ₁₅ R ₂	C ₁₀ R ₅	C ₁₀ R ₇	C ₂₅ R ₁₀	C ₁₀ R ₁₀
Cause B	0.97	0.72	0.35	1.67	1.16	0.61	1.02	1.67	0.49	3.58
C ₁₀ R ₁
C ₁₀ R ₂	-0.29
C ₂₅ R ₂	0.07	0.05
C ₅ R ₂	0.09	0.17	0.08
C ₇ R ₂	0.04	0.16	0.07	0.18
C ₁₅ R ₂	0.11	0.03	0.06	0.10	0.08
C ₁₀ R ₅	0.01	0.11	0.06	0.25	.	0.06
C ₁₀ R ₇	0.09	0.17	0.08	.	0.18	0.10	0.25	.	.	.
C ₂₅ R ₁₀	0.11	0.06	0.04	0.10	0.09	0.11	0.07	0.10	.	.
C ₁₀ R ₁₀	0.15	0.20	0.10	0.25	0.23	0.14	0.25	0.25	0.13	.

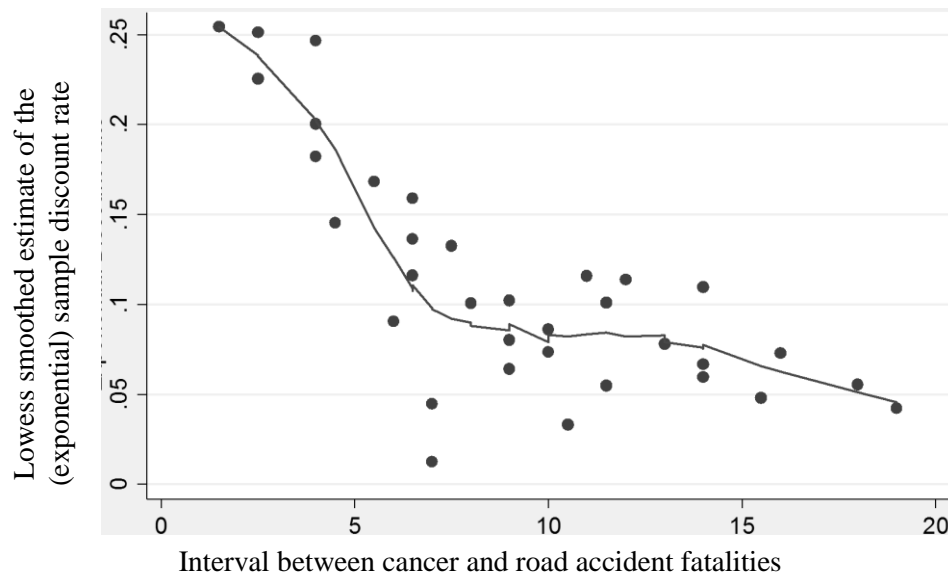
3

- 4 **Figure 3':** Matrix of elicited effective discount rates- sample level (subadditive exponential
 5 assumption), calculated using equation A3'''.
 6

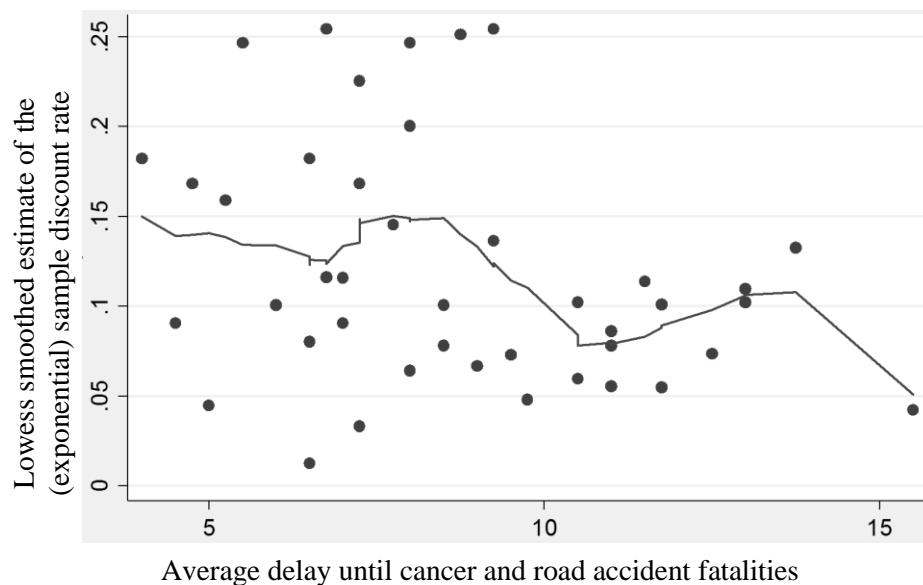
Cause A	C ₁₀ R ₁	C ₁₀ R ₂	C ₂₅ R ₂	C ₅ R ₂	C ₇ R ₂	C ₁₅ R ₂	C ₁₀ R ₅	C ₁₀ R ₇	C ₂₅ R ₁₀	C ₁₀ R ₁₀
Cause B	0.97	0.72	0.35	1.67	1.16	0.61	1.02	1.67	0.49	3.58
C ₁₀ R ₁
C ₁₀ R ₂	1.05
C ₂₅ R ₂	0.16	0.24
C ₅ R ₂	0.50	0.40	0.01
C ₇ R ₂	0.87	0.75	0.05	0.83
C ₁₅ R ₂	0.76	0.88	0.52	0.15	0.41
C ₁₀ R ₅	0.96	0.81	0.06	0.78	.	0.49
C ₁₀ R ₇	0.50	0.40	0.01	.	0.83	0.15	0.78	.	.	.
C ₂₅ R ₁₀	0.55	0.67	0.73	0.07	0.24	0.94	0.30	0.07	.	.
C ₁₀ R ₁₀	0.02	0.01	0.00	0.27	0.08	0.00	0.06	0.27	0.00	.

6

- 1 **Figure 4a:** Lowess smoothing sample average exponential discount rates against latency
- 2 differential (averaged across the two component relativities for each datapoint)



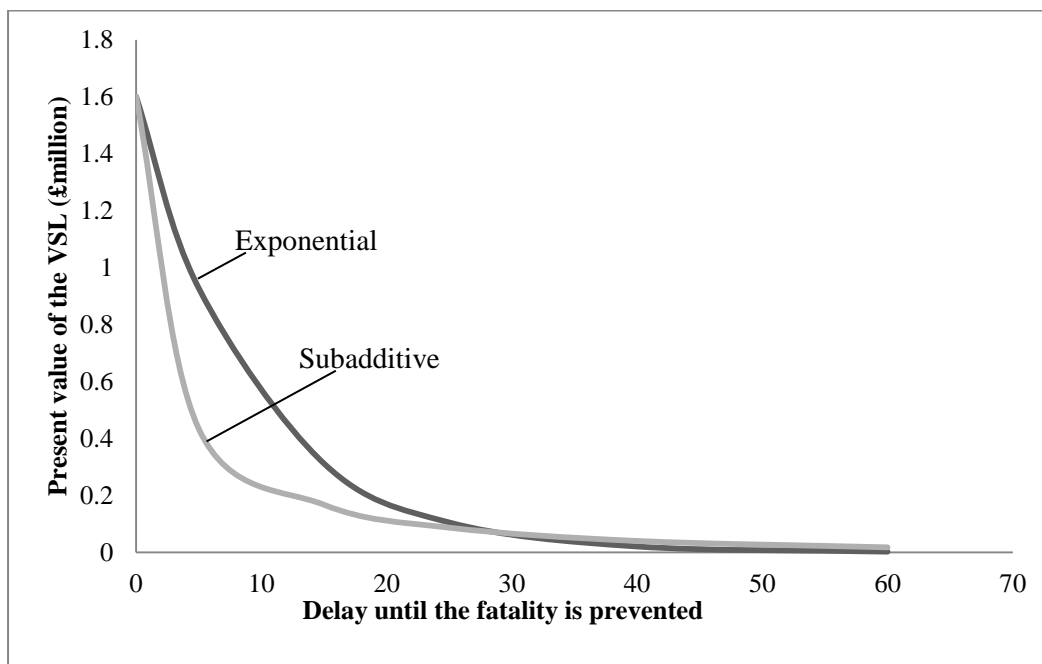
- 3
- 4 **Figure 4b:** Lowess smoothing sample average exponential discount rates against average
- 5 delay (averaged across the two component relativities for each datapoint)



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Figure 5: Implications of the exponential and subadditive assumptions on the discounted value of statistical life. The present value of the VSL for different delays is presented, using both the exponential and the exponential-based subadditive discounting functional forms. The discount factors used in these calculations are those elicited on an individual basis in this study (and presented in table 6), using geometric means. The input value is the UK Value of a Statistical Life, whose undiscounted value is £1.6 million.



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Tables

2 **Table 1:** Survey questions

Question number	Code	Delay until cancer fatality	Delay until Roads fatality	Interval (years)	Average Delay (years)
1	C ₁₀ R ₁	10	1	9	5.5
2	C ₁₀ R ₂	10	2	8	6
3	C ₂₅ R ₂	25	2	23	13.5
4	C ₅ R ₂	5	2	3	3.5
5	C ₇ R ₂	7	2	5	4.5
6	C ₁₅ R ₂	15	2	13	8.5
7	C ₁₀ R ₅	10	5	5	7.5
8	C ₁₀ R ₇	10	7	3	8.5
9	C ₂₅ R ₁₀	25	10	15	17.5
10	C ₁₀ R ₁₀	10	10	0	10

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1 **Table 2:** Demographics

Variable	Average
Gender (% female)	44.5%
Age (mean (s. dev.))	20.72 (1.82)
Household size (mean (s. dev.))	4.41 (1.74)
Rental (% rent)	75.2%
Personal income (monthly mean (s. dev.))	£616.76 (495.96)
Household income (monthly mean (s. dev.))	£3234.31 (2844.58)
Cancer personal experience* (%)	69.4%
Road accident experience* (%)	48.2%

2 *personal experience was defined as the respondent or a close friend or family member having experienced
3 cancer or a serious road accident. The UK incidence of cancer in 2011 was 331,487 while the number of people
4 reported to be injured or killed in a UK road accident in 2011 was 203,950. The ratio of experience reported in
5 our sample is in line with the national statistics (1.4:1 in our sample, 1.6:1 in the UK data).

- 1 **Table 3:** Geometric mean of relativities with latency and delay information. Information in
 2 the rightmost columns shows the excluded data, due to protest responses or extreme values.

Question	Code	Latency interval (years)	Average Delay (years)	Geometric mean	95% confidence interval	Excluded data Protests “Never switch”	Extremes “≥30 million”
1	C ₁₀ R ₁	9	5.5	0.97	[0.59, 1.60]	6	2
2	C ₁₀ R ₂	8	6	0.72	[0.42, 1.23]	7	1
3	C ₂₅ R ₂	23	13.5	0.35	[0.21, 0.59]	6	1
4	C ₅ R ₂	3	3.5	1.67	[1.08, 2.58]	6	1
5	C ₇ R ₂	5	4.5	1.16	[0.71, 1.89]	7	0
6	C ₁₅ R ₂	13	8.5	0.61	[0.37, 1.01]	5	1
7	C ₁₀ R ₅	5	7.5	1.02	[0.59, 1.77]	6	0
8	C ₁₀ R ₇	3	8.5	1.67	[1.00, 2.80]	8	0
9	C ₂₅ R ₁₀	15	17.5	0.49	[0.29, 0.83]	4	1
10	C ₁₀ R ₁₀	0	10	3.58	[2.37, 5.41]	14	2

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Table 4: Exponential, per-individual discount rate: fixed effects regressions (with robust standard errors) on scenario attributes, pooled discount rates

Discount rate	Model (1)	Model (2)	Model (3)
	N=4336	N=4336	N=4336
	R ² =0.0157	R ² = 0.0038	R ² = 0.0160
Latency interval	-0.012*** (0.002)	-	-0.013*** (0.002)
Average delay	-	-0.010** (0.004)	0.003 (0.004)
Constant	0.229*** (0.023)	0.207*** (0.035)	0.212*** (0.035)

1 **Table 5:** Classifications

Classification	Coefficient on Delay	Coefficient on Interval	N (% of usable sample of 104)
Exponential	insignificant	insignificant	36 (34.6%)
Hyperbolic	negative significant	unspecified	16 (15.4%)
Subadditive	unspecified	negative significant	43 (41.4%)
Both	negative significant	negative significant	2 (1.9%)
Other	Unspecified	Unspecified	7 (8.6%)

2

3

Table 6: Discount factors under exponential and subadditive (exponential-based) discounting assumptions

Time from the present (years)	Discount factor with Exponential assumption		Discount factor with Subadditive assumption	
	(geometric mean rate = 10.9%)	(median rate = 6.2%)	(geometric mean rate = 55.8%)	(median rate = 71.9%)
0	1	1	1	1
5	0.58	0.73	0.27	0.48
15	0.19	0.39	0.10	0.28
25	0.07	0.21	0.05	0.19
40	0.01	0.08	0.02	0.12
60	0.00	0.02	0.01	0.08

1 **Appendix 1: Eliciting exponential, hyperbolic and subadditive discount rates**

2 *Exponential*

$$3 \quad C_T R_t = \frac{(1+x)}{e^{\delta(T-t)}} \quad (A1)$$

4 To solve for δ , combining two relativities $C_T R_t$ and $C_{T'} R_{t'}$:

$$5 \quad \frac{C_T R_t}{C_{T'} R_{t'}} = \frac{(1+x)}{e^{\delta(T-t)}} \cdot \frac{e^{\delta(T'-t')}}{(1+x)} \quad (A1')$$

$$6 \quad \text{Letting } \frac{C_T R_t}{C_{T'} R_{t'}} = \varphi$$

$$7 \quad \varphi = e^{\delta[(T'-t')-(T-t)]} \quad (A1'')$$

$$8 \quad \delta = \frac{\ln \varphi}{[(T'-t')-(T-t)]} \quad (A1''')$$

9 *Hyperbolic*

$$10 \quad C_T R_t = (1+x) * \left(\frac{(1+\delta t)}{(1+\delta T)} \right)^{\gamma/\delta} \quad (A2)$$

11 To solve for δ , combining two relativities $C_T R_t$ and $C_{T'} R_{t'}$, and letting $\frac{C_T R_t}{C_{T'} R_{t'}} = \varphi$ gives:

$$12 \quad \varphi = \left(\left(\frac{(1+\delta t)}{(1+\delta T)} \right) * \left(\frac{(1+\delta T')}{(1+\delta t')} \right) \right)^{\gamma/\delta} \quad (A2')$$

13 Clearly this is a single equation in two unknowns (γ and δ) and as such cannot be solved as
 14 simply as the exponential equation. Commonly it is simplified in the literature using the
 15 assumption that $\gamma = \delta$.

$$16 \quad \varphi = \left(\frac{(1+\delta t)}{(1+\delta T)} \right) * \left(\frac{(1+\delta T')}{(1+\delta t')} \right) \quad (A2'')$$

17 This equation can be re-arranged into the standard quadratic form:

$$18 \quad (\varphi T t' - t T') \delta^2 + (\varphi T + \varphi t' - t - T') \delta + (\varphi - 1) = 0 \quad (A2''')$$

19

1 Using the quadratic formula:

$$2 \quad \delta = \frac{-(\varphi T + \varphi t' - t - T') \pm \sqrt{(\varphi T + \varphi t' - t - T')^2 - 4(\varphi T t' - t T')(\varphi - 1)}}{2(\varphi T t' - t T')} \quad (A2''')$$

3 This provides two solutions for δ in the hyperbolic case. In some cases, there is an
 4 unambiguous plausible δ . In other cases, we cannot say which of the two possible δ values is
 5 the most appropriate. In further cases, the elicited rate is negative which might indicate a
 6 legitimate preference for risk changes later, but might instead indicate that the data cannot be
 7 plausibly accommodated by the hyperbolic function (see Read and Roelofsma (2003) for a
 8 discussion of these issues). This is especially plausible since we do not find much empirical
 9 support for hyperbolic discounting when we analyse the exponential rates.

10 *Subadditive (exponential base)*

$$11 \quad C_T R_t = (1 + x) \delta^{(T-t)^s} \quad (A3)$$

12 where s is a parameter, typically between 0 and 1, which captures non-linearity of preferences
 13 over time.

$$14 \quad \varphi = \left(\frac{\delta^{(T-t)^s}}{\delta^{(T'-t')^s}} \right) = \delta^{[(T-t)^s - (T'-t')^s]} \quad (A3')$$

$$15 \quad \delta = \varphi^{\left[\frac{1}{(T-t)^s - (T'-t')^s} \right]} \quad (A3'')$$

16 Assuming $s=0.5$

$$17 \quad \delta = \varphi^{\left[\frac{1}{\sqrt{T-t} - \sqrt{T'-t'}} \right]} \quad (A3''')$$

18 From these equations, estimates of the discount rates under each assumption are calculated.
 19 We present the results in Table A1. The results, particularly the arithmetic mean,
 20 demonstrate that the subadditive rate is strongly influenced by high end outliers. The
 21 geometric mean is preferable because it includes all of the available data without being
 22 subject to the strong influence of high outliers.

Table A1 Discounting parameter summary: discount rates (%) are presented for the exponential, hyperbolic and exponential-based subadditive assumptions

	Arithmetic mean [95% C. I]	Median	Geometric Mean [95% C. I]
Exponential	12.2 [12.8, 12.4]	6.38	10.9 [10.8, 11.0]
Hyperbolic*	0.70 [0.50, 0.90]	0.112	0.150 [0.14, 0.16]
Subadditive exponential	472.8m [342.6m, 602.9m]	71.9	55.8 [54.2, 55.3]

*the hyperbolic case includes only the positive, unambiguous cases and cannot be meaningfully compared with the sub-additive and exponential cases.